COMBAT IDENTIFICATION
USING MULTIPLE TUAV SWARM

THESIS

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Abstract

In modern warfare, Tactical Unmanned Aerial Vehicles (TUAVs) are rapidly taking on a leading role in traditional and non-traditional ISR, to include Automatic Target Recognition (ATR). However, additional advancements in processors and sensors on TUAVs are still needed before they can be widely employed as a primary source for positive identification in the Combat Identification (CID) process. Cost is a driving factor for operating an ATR system using multiple TUAVs. The cost of high quality sensors appropriate for a single TUAV can be significantly higher than less sophisticated sensors suitable for deployment on a group, or swarm, of coordinated TUAVs. Employing two or more coordinated TUAVs with less complex sensors may lead to an equivalent or even better CID call than sending a single TUAV with more sophisticated sensors at a significantly higher cost. In addition, the coordinated TUAVs may be capable of reducing the time needed to correctly discriminate an object.

In our study we construct a simulation model of a single TUAV system with a high quality sensor and competing TUAV swarm systems using less capable sensors in Arena. We use the Boolean OR rule in our fusion algorithm to combine the declaration of sensors modeled in the swarm system. Five measures of performance (accuracy, number of TUAVs shot down, TUAV preparation time, mean of decision time, mean of simulated mission time) from the simulation models are collected to compare the swarm system to the single TUAV system. Statistical comparisons are conducted using a paired

t-test. The results illustrate improved performance of our swarm systems across most measures of performance.

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Younin Kang

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I. Introduction

1.1. Background

During Operation Iraqi Freedom some air-to-ground fratricide involving US pilots occurred. One of the worst incidents occurred when US Navy jets attacked Kurdish fighters and a group of US Special Forces (SOFs) leading a convoy of them in northern Iraq. US Special Forces sent two US fighter jets a message by radio to remove an Iraqi tank obstructing their way. But one of jets fired a missile at the Special Forces and Kurdish fighters, instead of dropping its bomb on an Iraqi tank. This incident resulted in 18 Kurds killed and three SOF injured. After making an investigation into the fratricide, the investigator announced that there was a simple communication mistake as a cause of incident. The radio of the US navy jet that had dropped a bomb on friendly forces was incompatible with the SOF. The SOF could communicate only with USAF aircraft in that operation. Furthermore, although the vehicles carrying the friendly fighters was marked with clear fluorescent-orange, the fighter aircraft could not identify them, because dust and low clouds had obscured the pilots' vision [1].

According to US Army TRADOC Fratricide Action Plan, "Fratricide is the employment of friendly weapons and munitions with the intent to kill the enemy or destroy his equipment, or facilities, which result in unforeseen and unintentional death or injury to friendly personnel." The incident of fratricide has continuously happened as a

result of warfare on a battlefield. Especially in ground-to-ground or air-to-ground engagements, one of the important tasks for the efficient conduct of modern warfare is to preclude or reduce such misshapes from occurring. Aircrafts fly faster and Tanks fire at longer rages. Their precision and lethality have been increased through advances in technology. In addition the capability to identify friend-or-foe has made startling progress. Nevertheless, the lack of target identification and situational awareness on the battlefield occasionally results in fratricide. As seen in combat history, fratricide will never totally be eliminated, but the number of occurrences of fratricide can be reduced via development in technology for Combat Identification (CID) along with enhanced training.

When Army combat commanders are asked what has contributed most to their victory in Iraq, they often respond that it is Intelligence, Surveillance, and Reconnaissance (ISR). This comes from the coordinated use of Unmanned Aerial Vehicles (UAVs) (from Ravens to Global Hawks), manned aircraft carrying cameras, electric sensors, and many other assets for ISR [2].

In July 2008, in an interview with The Hill (a congressional newspaper), Air Force Lt. Gen. Michael Peterson said, "*What we did is we took an end-to-end look at what we could provide and what we can deliver in terms of ISR. The highlight of that is the importance of full-motion video to the ground force. Today most of that is done with the Predator [unmanned aerial vehicle (UAV)]. Global Hawk [UAV] has still images, but we also moved on with a few aircraft called Reaper [UAV], which is the follow-on generation to the Predator*." [3]. UAVs are more often being used for military purposes, like search and surveillance in the battlefield. They play a decisive role in information

collection from hostile and unknown areas.

1.2. Research problem

In modern warfare, UAVs are rapidly taking on a leading role in traditional and non-traditional ISR, to include Automatic Target Recognition (ATR). With the development of technology, the processors and sensors on UAVs have been improved, however, advancements are still needed before they can be widely employed as the primary or perhaps sole source for positive identification in the CID process.

The CID process strongly depends on the ability of the sensors to determine the identification of objects. Poor sensor information will result in poor performance in the CID process. Fused sensors from coordinated UAVs can provide more information than the sensor with a single UAV. Cost is a driving factor for operating an ATR using multiple UAVs. The construction cost of such an ATR system relies on the quality of sensors, airframes, and many other components. However, sending two or more coordinated UAVs with less complex sensors may lead to an equivalent or even better CID call than sending a single UAV with more sophisticated sensors at a significantly higher cost. In addition, the coordinated UAVs may be capable of reducing the time and the number of UAVs needed to correctly discriminate an object.

We expect that a swarmed system [4] incorporating the capabilities of multiple UAVs to cooperatively perform ATR will decrease simulated mission time and increase likelihood of making the correct CID call for selected scenarios.

1.3. Scope

The scope of this thesis is to analyze multi-agent UAV swarm to understand the effects of changing defined variables in CID process, including True Positive Rates (TPRs) in the discrimination process for scenarios with varying number of enemies. The analysis includes construction of a detailed computer simulation of the entire CID process in Arena for a scenario with only enemies present. The model is used to explore major factors that affect the decision time and the correct CID call. This analysis examines the feasibility of ATR using a UAV swarm compared to ATR using a single UAV for a variety of performance measures and provides insight into developing a strategy to improve ATR performance in such a system.

1.4. Thesis Organization

The remainder of this document is organized as follows. Chapter 2 presents a literature review including an introduction of system, model, and simulation, an overview of Arena as a simulation tool, a description of CID, and an introduction of a Tactical UAV (TUAV) and ATR. It also contains an overview of a method to perform fusion and common technique used to assess ATR performance. Chapter 3 presents a methodology for constructing the simulation model in Arena. Chapter 4 provides the results and analysis of simulation. Finally, chapter 5 presents a summary of contributions and findings along with thoughts for the continuation of related research.

II. Literature review

Introduction

This literature review is arranged with the following primary sections. Section 2.1 provides a review of the subjects related to system, model and simulation. Section 2.2 provides an overview of Arena, a simulation software package, used to build the CID model. Section 2.3 provides a description of CID. Section 2.4 provides a general knowledge of TUAV and ATR. Finally, section 2.5 presents an overview of the method to perform fusion and common techniques used to assess ATR performance.

2.1 System, Model and Simulation

A system that relies on the objective of a particular study is defined as a collection of entities which interact each other toward the attainment of some logical end. The state of a system is a collection of variables necessary to describe a system at a particular time. For example, in a study of a bank, if one wants to decide the number of tellers needed to provide adequate customer service, the system can be described as a portion of the customers waiting in line or being served and the tellers. In addition, the tellers and the customers can be defined as objects and examples of possible state variables are the time of arrival of each customer and the number of tellers in the bank [4:3].

A model is defined as a simplified representation of a system at some particular point in time or space intended to promote understanding of the real system. Modeling, especially scientific modeling implies the process of generating a model as a conceptual

representation of some phenomenon. This conceptual model is used to implement computer simulation that describes the behavior of a system over time. In general one builds a model, simulates it, gets something by simulating the model, revises the model and proceeds the iteration till a sufficient level of understating is obtained.

Figure 2.1 maps out diverse ways in which a system might be studied in order for one to get some insight into the interactions or relationships among various components, or make a prediction for the performance under new conditions being set.

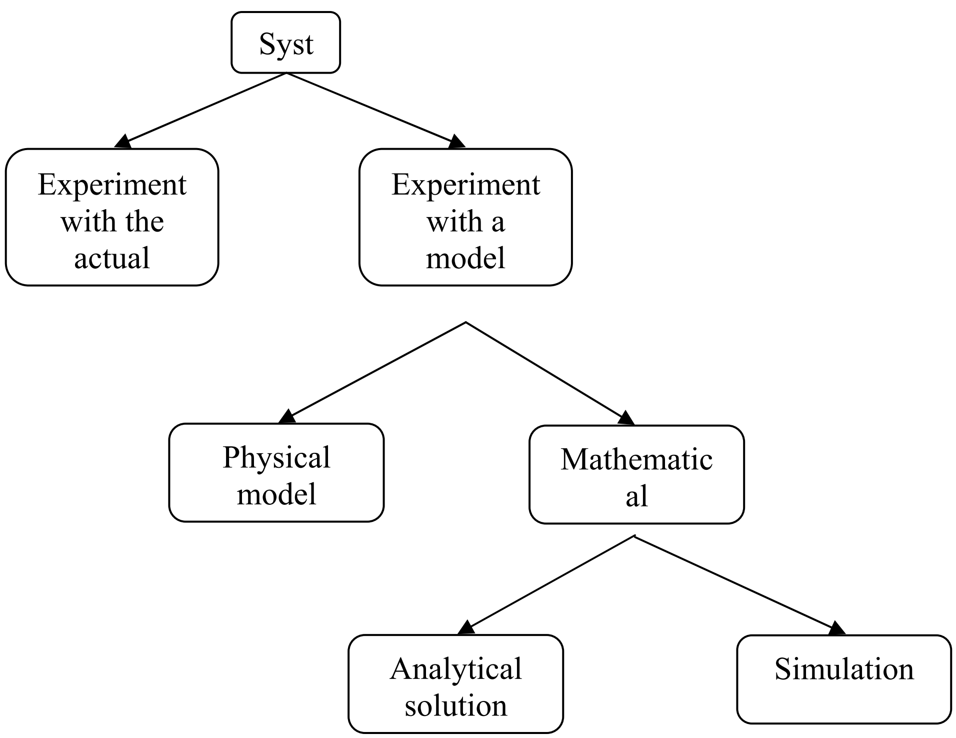

Figure 2.1 Ways to study a system [4:4]

2.1.1 Simulation

“Simulation refers to a broad combination of techniques and applications to imitate the real systems. Simulation is usually implemented on computer by using several available software tools. Furthermore, it can be said that simulation is a general expression since the idea finds its applications across many fields and industries” [5]. If the mathematical or logical relationships that constitute a model are simple enough, mathematical methods, e.g., probabilistic theory or algebra would be fine with one who wants to gain some understanding about behavior of the model. However, because most real systems are too complex, realistic models cannot be evaluated analytically, and these models should be studied by simulation. Applications for simulation are huge and various. Its examples are listed below [4:2].

- Designing and analyzing manufacturing systems
- Evaluating military weapons system or their logistics requirement
- Analyzing supply chain
- Determining hardware and software requirements for a computer system
- Evaluating designs for service organizations such as contact centers, fast-food restaurants, hospitals, and post offices

2.1.2 Simulation Classifying

Simulation is classified along three different dimensions as discussed below [4:5].

- *Statistic vs. Dynamic Simulation Models.* A static simulation model represents a system at a specific time, or used to represent a system where time plays no role. Monte Carlo models are good examples of a static simulation. On the other side, a

dynamic simulation is defined as a depiction of a system where it evolves over time, such as a queuing system in a bank.

- *Deterministic vs. Stochastic Simulation Models*. A deterministic simulation model is defined as a simulation model does not include any probabilistic components. Once input quantities and relations in deterministic models are detailed, the output is determined. If a simulation model contains some random input components, it is called stochastic. A stochastic simulation model produces output that is itself random.
- *Continuous vs. Discrete Simulation Models.* A discrete simulation model has state variables changing only at a countable number of points in time. These points in time are the ones at which the events occur, or change in state. On the other hand, if the state variables change in a continuous way, it is a representation of a continuous simulation model.

2.1.3 Discrete Event Simulation

In a discrete event simulation, the system operation is defined as a chronological sequence of events. Each event occurs at an instant in time and marks a change of state in the system [6]. "Though simulation has been applied to a great diversity of real world systems, discrete event simulation models all share a number of common components and there is a logical organization for these components that promotes the programming, debugging, and future changing of a simulation model's computer program" [4:9]. In most discrete-event simulation models, the following components are found.

- *System state*: The collection of state variables necessary to describe the system at

a particular time.

- *Simulation clock*: A variable giving the current value of simulated time.
- *Event list*: A list containing the next time when each type of simulated Time.
- *Statistical counters*: Variables used for storing statistical information about system performance.
- *Initialization routine*: A subprogram to initialize the simulation model at time zero.
- *Time routine*: A subprogram that determines the next event from the vent list and then advances the simulation clock to the time when that event is to occur.
- *Event routine*: A subprogram that updates the system state when a particular type of event occurs (there is one event routine for each event type).
- *Library routines*: A set of subprograms used to generate random observations from probability distributions that were determined as part of the simulation model.
- *Report generator*: A subprogram that computes estimates of the desired measures of performance and produces a report when the simulation ends.
- *Main program*: A subprogram that invokes the timing routine to determine the next event and then transfers control to the corresponding event routine to update the system state appropriately.

Figure 2.2 shows the logical relationships among these components. First of all, the initialization routine is invoked in the main program, and the simulation starts at the time zero, where the simulation clock is set to zero, the simulation initializes the system

state, statistical counter, and event list. Then, the main program takes control in order for it to invoke the timing routine to decide the next event time. If event type *i* is the next to occur, the time routine advances the simulation clock to the time that an event *i* will occur, and event routine *i* is invoked by the main program. After the system state and the statistical counters gathering information about performance of system are updated, the occurrence time of future events are generated, and the information is added to the event list. Then, if the stopping conditions are satisfied, the estimates (from the statistical counters) of performance measure and a report are, respectively, computed and made by the report generator. On the other hand, if the conditions for termination are not enough, the main program is invoked from the event routine *i* and all processing is repeated until the stopping conditions are met.

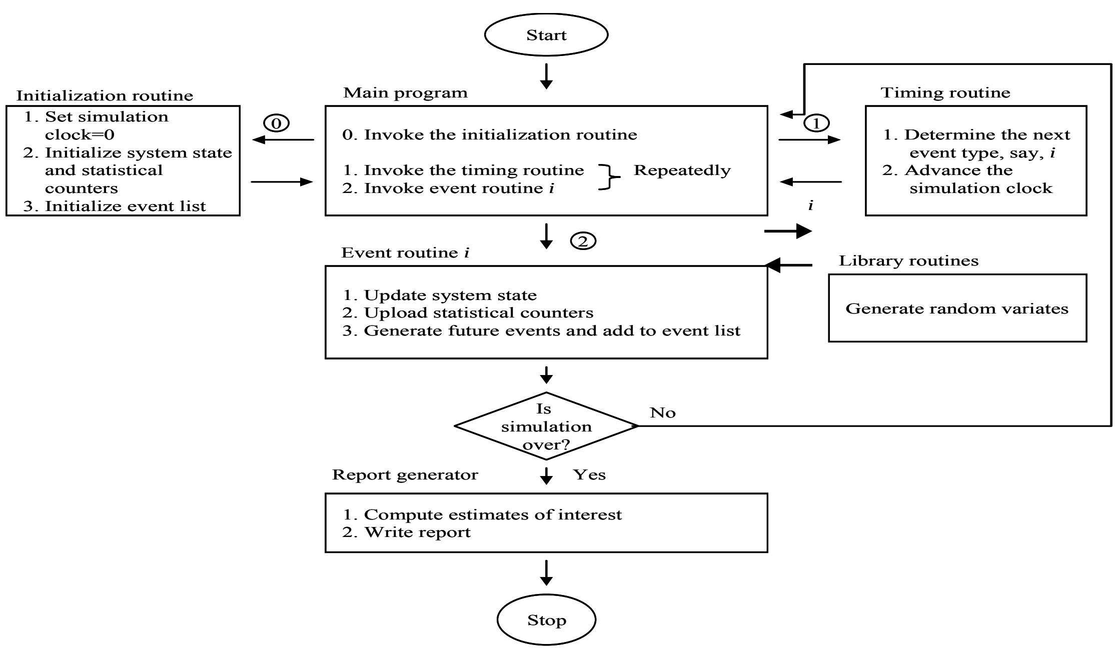

Figure 2.2 Flow of control for the next-event time-advance approach [4:10]

2.2 Overview of Arena

Arena 10 is used for the development and analysis of this research. This simulation and automation software using the SIMAN processor and simulation language is developed by Rockwell Automation. Arena is widely used to simulate a company's process, such as manufacturing plants, to analyze its current performance as well as possible changes that could be made. By accurately simulating a process, a company can see the outcome of changes without implementing them in real-time, thus saving valuable time and resources.

With Arena, the user can build their model by dragging module representing process or logic from the Project Bar into the Model Window Flowchart and placing it and simulate the performance of the system to understand complicated relationships and figure out opportunities for improvement. Besides, since it can visualize the operation with dynamic animation graphic, this feature gives the user more clear understanding and helps the user check model verification. Finally, to decide the best way, the user analyzes how the system will perform in its various configurations and under a myriad of possible alternatives [7].

Arena itself has three additional tools for analyzing data or performance measures. Firstly, the input analyzer is used to determine the best fit of probability distribution functions to input data. Besides, it can generate random data, such as a set of inter-arrival time or process time, to be analyzed. The output analyzer component of Arena is used to display output data so that it allows the user to view and analyzed his data quickly and easily. Lastly, if the simulation model is completed, validated and configured properly for use by the process analyzer, the process analyzer is used to

compare the outputs from validated models based on different model inputs, such as different process times and possible number of teller in a bank and etc., or scenarios.

2.3 Description of Combat Identification

Sensors, communications and computation systems to provide situational awareness of battle space are combined in network centric warfare (NCW). One of elements of the awareness is known as CID to indentify friendly combat entities or enemies.

CID is defined as a process of attaining accurate characteristics of objects detected in the battle-space and identifying the objects as friends, neutrals and enemies. CID must be performed in the all of mission area including air, land and sea in order for commanders to timely decide their COA on enemy action and to effectively employ their forces and weapons and to minimize friendly force's casualties.

2.3.1 Taxonomic Relationships Defined

As shown in Figure 2.3, identity can be described by seven states. Each object detected is identified as one of them consisting of hostile, neutral and friendly. It refers to where the object is detected and which type of object is at different levels of detail from platform type like fighter. Nationality implies that which country the aircraft belongs to. Finally, activity mission tells for what the aircraft is doing such as air patrol or strike.

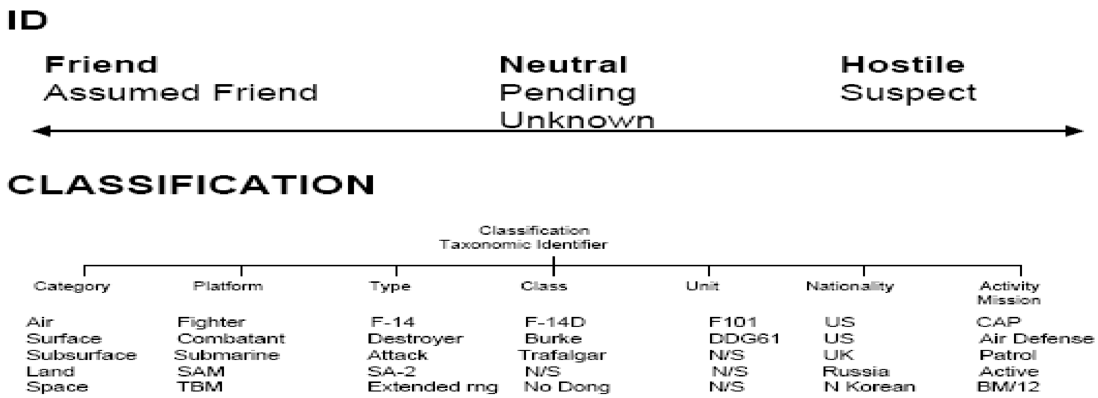

Figure 2.3 Combat ID Taxonomy [9]

2.3.2 Outline of CID Process

The entire concept of CID is shown in Figure 2.4. The “Direct” ID source comes from sensors equipped with the platform of shooter but the “Indirect” ID source refers to off-board. Single or multi sources of ID information each have some probability of correct ID are fused to provide an overall statistical declaration of the identity. Then, the engagement rules are applied and if it is within threshold for statistical declaration, firing decision will be given.

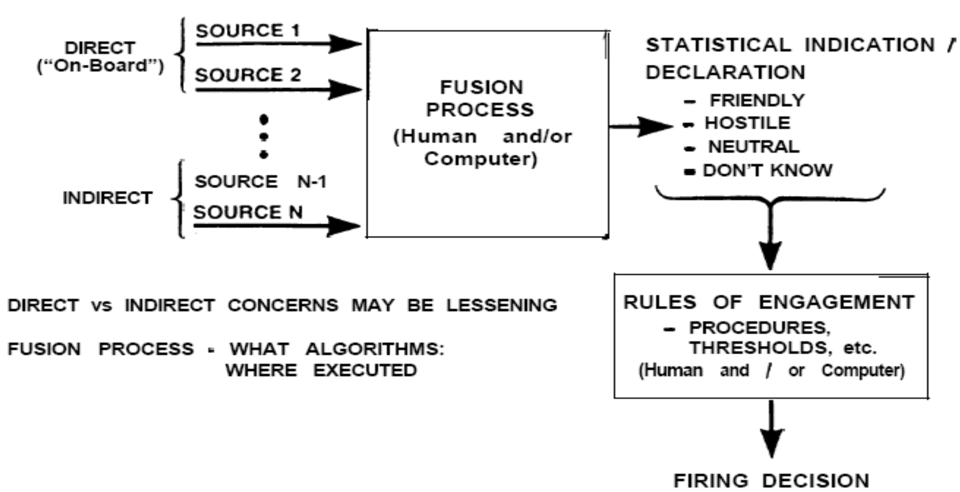

Figure 2.4 Combat Identification Process [10]

2.3.3 Air to Ground (A/G) CID Scenario

Though there are several CID scenarios such as Air to Air and Air to Ground and etc, this section will cover only A/G scenario of CID, because this research is a flavor of A/G CID. The A/G CID architecture consists of three platforms: a Forward Air Controller (FAC) being assumed to a ground FAC, A/G shooter being a fixed-wing aircraft, and A/G surveillance by Off-board sources or UAVs. Each of the platforms is connected to each of the other platforms to pass data in all nodes. Given an object detected, a fusion algorithm is applied to combine various sources from cooperative and non-cooperative systems. If it is declared as a target, CID information will be transferred to a warfighter to let him know all information of the target. After all, he will shoot the target and completes his mission.

2.3.4 Introduction to Automatic Target Recognition

As mentioned above, Combat ID uses both cooperative system and non-cooperative identification methods. Identification Friend or Foe (IFF) system is an example of cooperative systems. This system inquires it using electronic communication between two friendly systems to identity a potential target. If there is no feedback, non-cooperative means must be made.

Non-cooperative means can be performed by a man-in-the-loop, autonomously by an identification system, or by both. One possible man-in-loop mean is for the pilot to visually confirm the potential target before engagement. An Automatic Target Recognizer (ATR) is considered to be a case of non-cooperative Combat ID performed by an autonomous system [11:2].

Military ATR systems have been around since the early 1960's [12]. Laine [11] states, "improved ATR systems would help streamline the Combat ID process and allow the USAF to use Global Hawk at more than the one-third capacity used during Operation Iraqi Freedom (OIF)."

Figure 2.5 shows a notional ATR system with sensors. One or multi sensors on the same of different platforms are assigned to the Region of Interest where potential targets can be located. Then, the system performs detecting, tracking and classifying them. The ATR system is suggested that it contain a minimum of three output labels: Target, Non-Target, and Non-declaration. According to USAF doctrine, a desired level of confidence in declaring the object is needed before making a fire decision [13], [14]. When "non-declaration" is labeled due to lack of confidence, the ATR system may keep watching to get more information. In these situations, the current ATR system takes multiple looks of the same target within limited time, since other platforms may not be available to help in the ID process [11:5].

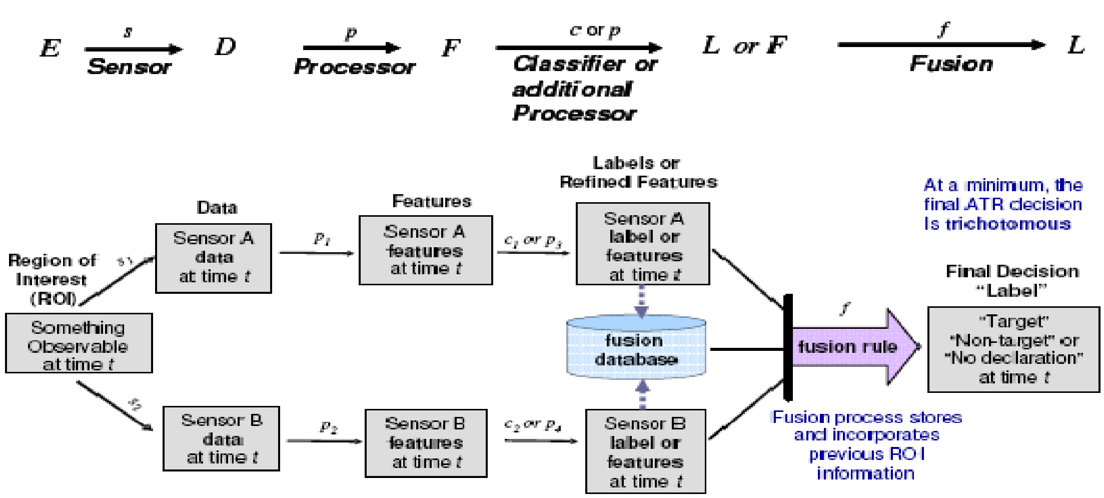

Figure 2.5 Notional ATR System with Sensors A & B Collecting Data through Time [11]

2.4 Data Fusion for Automatic Target Recognition.

Lots of quantitative techniques are available to implement fusion at various levels. It is important for one to find the best technique for a given application. All the data fusion communities do not agree about which fusion methodology is best for the application [15]. However, if the individual sensor data is refined to create a class label, then the Boolean voting logic is considered as a standard fusion methodology to figure out a single class estimate [16], [17], [18].

2.4.1 Boolean Fusion Methodologies for ATR System

Boolean rules can be used as a method of combining output labels of distinctive identification systems. The followings are examples of Boolean fusion rules.

- *Logical AND*. If and only if all of the sensor labels denote the target is a "Hostile", the unknown objective is identified as a Hostile target. This rule may be called as the AND rule.
- *Logical OR*. If any of the sensors classify it as a "Hostile", then the system concludes an object is a "Hostile." This rule may simply be referred to as the OR rule.
- *Majority Vote*. A majority of the sensors is required to determine the target as a "Hostile." For example, 2 or more "Hostile" label are needed for a three sensor suite to declare "Hostile."
- *Sensor Corroboration*. The fusion logic related to sensor corroboration requires one of the sensor not only to declare a target as a "Hostile" but also to corroborate

this label with one of others. As mentioned by Hill (2003), such a fusion rule may be appropriate when sensors do perform different function in discriminating an object.

- *Sensor dominance*. This fusion logic may be appropriate in the case that one sensor performs better than others. For example, sensor A has high confidence and declares a fused "Hostile" label regardless of the labels from sensor B and C.

Figure 2.6 for the use of three sensors (S^A, S^B and S^C) depicts an illustration of Boolean logic fusion rules for the use of three sensors. Positive declarations of "Hostile" targets are represented by the grey areas for each of the Boolean fusion rules.

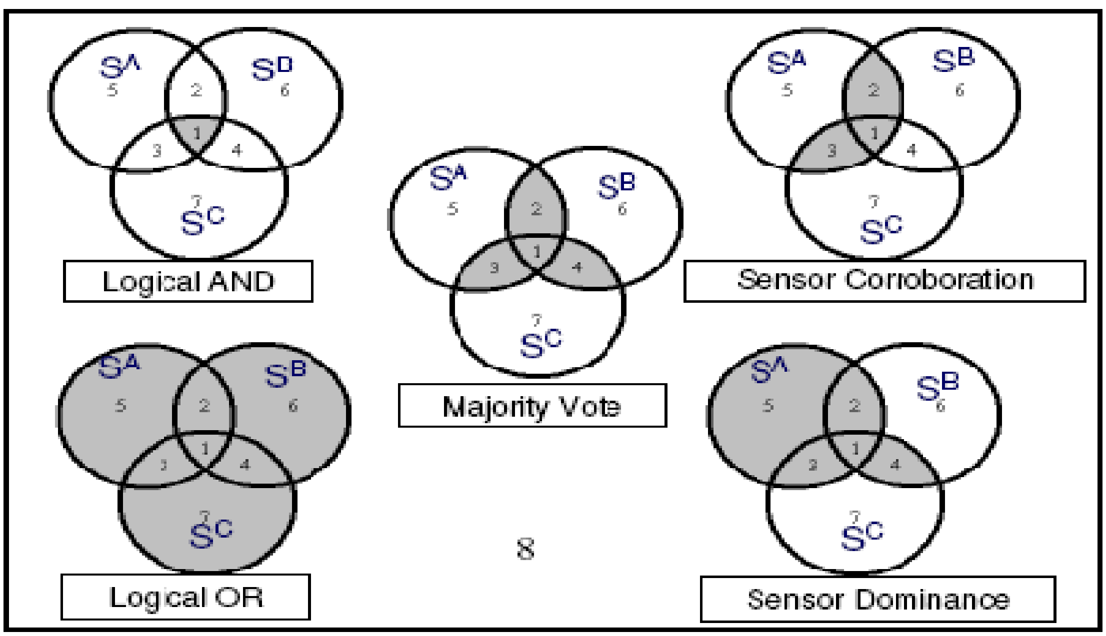

Figure 2.6 Examples of Various Boolean Fusion Rules with Venn Diagrams [11:45]

2.4.2 Mathematical Framework for 3-Class Data Fusion Experiment

Various classification problems have been modeled at the top-level using 2-classes. An ATR system declaring an unknown object as a target or non target is an example showing a 2-classes model above. However, before an ATR system declares an unknown object as a target and it is engaged, a minimum level of confidence is required by the USAF. Consequently, three output classes including “Target,” “Non-target” and “Non-declaration” are required to explain for those cases when the confidence is not satisfied. Figure 2.7 shows a sample of 2-class confusion matrix with a “Non-declaration,” with a column for each labeled class and a row for each true class. For most applications, warfighters perform horizontal analysis, but engineers are concerned with vertical analysis of the confusion matrix yields the estimates of error from the number of class labeled. The error rates are calculated as conditional probabilities using Bayes rule with other prior probabilities of class membership (denoted P_T and P_F).

Classifier “Labels”

True Classes	*"Target"*	*"Friend"*	*“No declaration”*	Horizontal Totals
Target	Target labeled "Enemy"	Target labeled "Friend"	Target labeled “Unknown”	Target evaluated
Friend	Friend labeled “Target”	Friend labeled "Friend"	Friend labeled “Unknown”	Friend evaluated
Vertical Totals	"Target" declared	"Friend" declared	"Unknown" declared	

Legend	Contribution	Analysis
	Correct ID	Horizontal
	Critical Error	Vertical
	Non-Critical Error	Vertical
	Non-Declaration	Horizontal
	Totals	H or V Analysis

Figure 2.7 Confusion Matrix with Rejection and Error Contributions [11:121]

The critical and non critical errors will be defined as below.

- Probability of a Critical Error: the probability of classifying a Friend as "Target", such a case like fratricide,

$$\hat{P}(E_{CR}) = \frac{Number\ of\ Friends\ declared\ as\ "Target"}{Total\ nuber\ of\ \text{"Target" declarations}}$$

$$= \frac{P_F \hat{P}_{FP}}{P_F \hat{P}_{FP} + P_T \hat{P}_{TP}}, \tag{2.1}$$

- Probability of a Non Critical Error: the probability of classifying an Enemy as a Friend, for example lost opportunities to engage the enemy,

$$\hat{P}(E_{NC}) = \frac{Number\ of\ Targets\ declared\ as\ "Friend"}{Total\ nuber\ of\ \text{"Friend" declarations}}$$

$$= \frac{P_T \hat{P}_{FN}}{P_F \hat{P}_{TN} + P_T \hat{P}_{FN}}, \tag{2.2}$$

and the probabilities of False Negatives and True Negatives are, $\hat{P}_{FN} = \hat{P}_{FN}(\theta) = 1 - \hat{P}_{TP}(\theta)$ and $\hat{P}_{TN} = \hat{P}_{TN}(\theta) = 1 - \hat{P}_{FP}(\theta)$. If it is assumed that all objects belong to one of the true classes, $\hat{P}_{Dec}$, the probability of declaration, can be used as a performance measure of the "Non-declaration" labels. The probability of rejecting a sample is related as:$\hat{P}_{REJ} = 1 - \hat{P}_{Dec}$. The probability of a declaration is then:

- Probability of a Declaration: the probability of either class being declared "ND"

$$\hat{P}_{Dec} = \frac{Number\ of\ objects\ declared\ as\ "ND"}{total\ objects\ evaluated}$$

$$= P_T \hat{P}_{UT} + P_F \hat{P}_{UF}, \tag{2.3}$$

where $\hat{P}_{UT} = \hat{P}("ND"|T)\ and\ \hat{P}_{UF} = \hat{P}("ND"|F)$. Given all probabilities calculated from test, $P = \hat{P}$ will be assumed for the remainder.

2.5 Concept of Tactical Unmanned Aerial Vehicle (TUAV)

TUAV is designed to be a ground maneuver brigade commander's UAV, providing him with a number of benefits to include: enhanced enemy situational awareness, a target acquisition capability, battle damage assessment (BDA), and enhanced battle management capabilities (friendly situation and battlefield visualization). TUAV gives the commander "dominant eye" allowing him to see into area where the commander does not want to send ground reconnaissance elements or manned aerial platforms. It can be linked to and cued by sound IPB and wide area sensors such as JSTARS Common Ground Station (CGS), Artillery Counter Mortar/Battery Radars, and Forward Area Air Defense System (FAADS) for distribution via intelligence channels.

The system is designed for ease in launching, operating, recovering, and maintaining with minimal training, logistics, and personnel. To reduce its footprint, tear down in rapid, deploy and set up, and minimize impact on brigade combat service support (CSS) resources, it presents a small profile in battlefield.

A TUAV system consists of four basic components: Ground Control Stations (GCS) and related equipment, Air Vehicles (AV), Modular Mission Payloads (MMP), and communications. The TUAV baseline is to provide 12 hours of continuous operations within a 24-hour period. For no more than three consecutive days, the system is capable of surge operations for 18 hours per 24-hour period, and the following day is limited to 8 hours of operation. A full baseline requires a crew of approximately 22 for operation and maintenance at the operational tempo above.

2.5.1 Air Vehicle

The air vehicle (Figure 2.8), constructed of composite materials and powered by a rotary engine, is a mid-wing monoplane with a twin boom empennage supporting an inverted-V tail. The TUAV system has four-hour endurance with a range of 50 kilometers from the launch and recovery site. It is operated with clear line of sight between the air vehicle and ground data terminal/portable ground data terminal [19]. Though it is not designed to meet the requirements of low signature, due to composite materials and its small size, it can reduces signature characteristics and is not visually detectable from range exceeding 4,000 ft and not audible from ranges exceeding 2,000 ft. It is capable of operating during less than ideal weather conditions, such as moderate rain condition, within its radius of action. Nominal operating/survivable altitudes for day and night operations are respectively from 8,000 to 10,000 feet Above Ground Level (AGL)/from 6,000 to 8,000 feet AGL. Heavy icing, precipitation, or high surface winds may prevent launches or operations in some areas.

Figure 2.8 Air Vehicle [20]

2.5.2 Modular Mission Payloads (MMPs)

The baseline sensor of the TUAV is the Electro-Optic/Infrared (EO/IR) payload (Figure 2.9). The payload is a multi-mode, Forward Looking Infrared (FLIR) / Line Scanner / TV sensor. It is required to have resolution enough to detect and recognize an Armored Personnel Carrier (APC) sized target at the operational altitudes of day and night operation and at survivable standoff ranges (3-5km) from imaged target. In EO and IR mode, the requirements are respectively for 80 percent probability of detection at 3.8 km and 70 percent of that at the targeted range of 3.5 km [18]. It is capable of autonomous preplanned operation and instantaneous retasking throughout a mission. In addition, it can provide continuous zoom capabilities when in EO mode and multiple Fields of View (FOV) when in IR and slew 360 degrees.

Figure 2.9 EO/IR Payload [20]

The payload of secondary priority is a Synthetic Aperture Radar/Moving Target Indicator (SAR/MTI). This payload increases situational awareness by providing high-resolution imagery enough to detect and recognize APC sized target at operational altitudes and survivable standoff range in this situation, e.g., adverse weather or

battlefield obscurants. The MTI adjunctive to Joint Surveillance and Target Attack Radar System (JSTARS) serves as an immediate cure to potential threat activity. If it detects and recognizes threat activity, the activity can be confirmed by onboard EO/IR or SAR sensors.

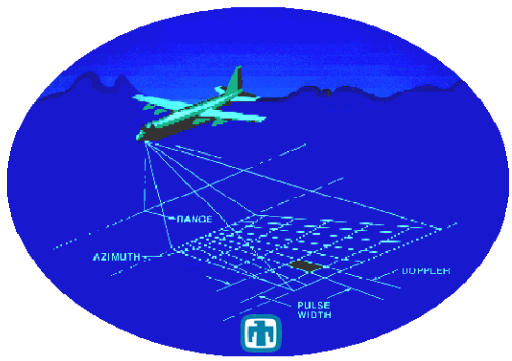

Figure 2.10 Synthetic Aperture Radar Imaging Concept

Michael P. Farmer [21:69] states, “A TUAV payload that incorporates a SAR, which is one of the future payloads being designed for the TUAV, combined with an ATR system at the GCS, could provide this solution (to reduce / remove the role of the man in the loop in the CID process) in the near future.” According to Sandia National Laboratories [23], the expected appearance of target vehicles in SAR imagery are modeled and quantified. Match metrics, derived from mathematical principles, measure a level of agreement between target models and potential targets detected in new SAR imagery.

The TUAV Communications/Data Relay payload is used to provide Very High Frequency/Ultra High Frequency (VHF/UHF) beyond line of sight relay for

communications, supporting extended range operations of Army XXI with communication while operating on board the TUAV.

2.5.3 Ground Control Station (GCS)

A GCS is designed for two primary functions. The first primary function is to control, track, and operate the AV. Second, it is used to manipulate the payload, receive, and process telemetry and video downlinks. In addition, it can call for and adjust indirect fire.

TUAV system has two GCSs, each in a High Mobility Multipurpose Wheeled Vehicle (HMMWV) mounted Command and Control ($C^{2)}$ shelter. The GCS consists of two operator positions, an air vehicle operator position and a Mission Payload Operator (MPO) position. Since both positions are identical in capability, functions can be transferred to either when one operator position fails. It can not only control and communicate with one AV at a time but also control another AV while another GCS prepares its AV for launching or recovering. As long as there is line of sight path between the Ground Data Terminal (GDT) and the AV, the AV is controlled through the GDT to distances up to 50 kilometers.

Figure 2.11 Ground Control Station (GCS) – Interior View [20]

2.5.4 Ground Communications

The GCS provides easy interface to the existing secure command, control, communications, computers, and intelligence (C4I) architecture. It includes Common Ground Station (CGS), Advanced Field Artillery Tactical Data System (AFATDS), All Source Analyses System (ASAS), Forward Area Air Defense System (FAADS), and Army Airspace Command and Control (A^2C^2). Various communication systems including secure voice, electronic dissemination, and video in the GCS are used for intelligence reports. Secure communications and intelligence dissemination are provided through the standard DoD tactical (VHF and UHF) radios, Mobile Subscriber Equipment (MSE), and the Tactical Local Area Network (TACLAN). TUAV communications must interface with selected standard DoD C4I systems, National Security Agency approved encryption systems, and etc.

The tactical communication system gives TUAV tactical users integrated communication for mission support and communication between GCSs. Radio communications between operators in GCS, external system users, and support units are performed through Single Channel Ground and Airborne Radio System (SINCGARS) radios. The Single Unit Transceiver radio (SUT) provides external voice communications on the flight line.

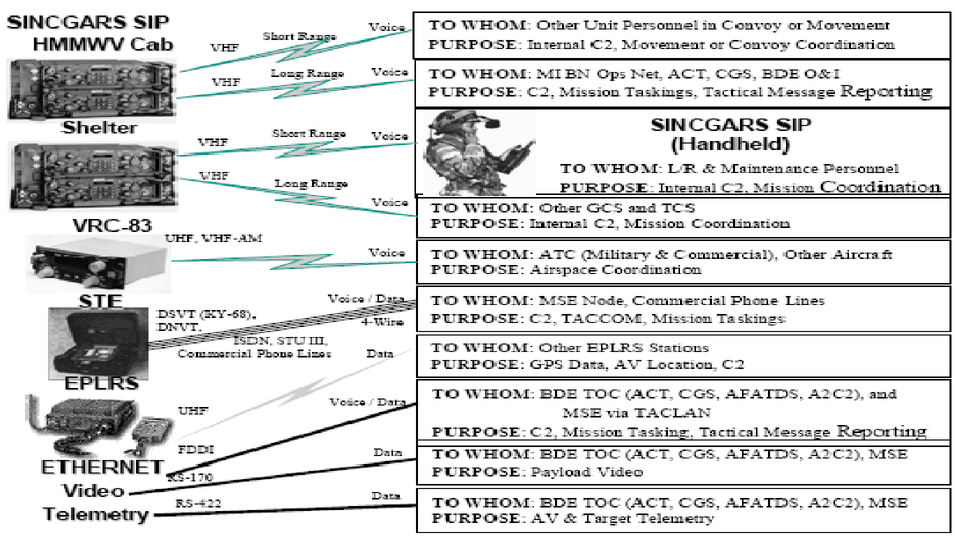

Figure 2.12 GCS Radios and Communications Devices [19]

Telephones can be also used for communication between the TUAV Control Shelters, Mobile Maintenance Facility, and system users. A tactical telephone as a part of the TUAV system is capable of handing digital data and voice communication. There are two telephone networks available: Mobile Subscriber Equipment (MSE) for telephone (voice/data) communication and one fiber optic net (Ethernet) for intra shelter voice/data communication.

III. Methodology

Introduction

Chapter 3 presents our methodology for analyzing TUAV swarm with low-value sensors versus a single TUAV with a high-value sensor and how our simulation model was constructed. This chapter consists of four sections; the first provides a conceptual model description and assumptions for the simulation model, the second section focuses on the steps of building the simulation model using Arena, the third covers specific variables and statistics used for our study, and finally the fourth section discusses verification and validation of the model.

3.1 Model Description and Assumptions

Our CID process begins with a wide area sensor's (such as JSTARS) reception of Moving Target Indicator (MTI) data. This data from the JSTARS platform is transferred to the JSTARS CGS located at a Brigade Tactical Operations Center (TOC). A decision maker, such as Brigade Commander, Executive Officer, or Operational Officer, at the TOC has to decide if he develops the MTI item further or not. If he decides to further develop it, he may use one of their internal assets (i.e., TUAVs or ground reconnaissance units) to gain more information on the MTI or request additional intelligence an outside agency such as satellite imagery. If tasked to the TUAV, the item is routed to a GCS. All TUAVs (the single system or the two system swarm) are assumed to use the same platform and assumptions for preparation time, and time to travel to target area, etc. The only modeled difference is in terms of better (at a significantly higher cost) sensor

capabilities on the single system TUAV. In the case of single TUAV system, on receiving an MTI, a GCS prepares to launch its TUAV and send it to a mission area. After preparation, a TUAV moves to the mission area and begins the discrimination process in a Region of Interest (ROI). We define the discrimination process as the TUAV declaring (labeling) the MTI data as an enemy (target) or not. For this study every MTI is considered to be a true enemy and all MTIs occur within the defined ROI. Once in a position to begin its mission execution, a TUAV may be shot down by air defense weapons of an enemy. This is modeled through use of a defined effective area for an enemy air defense system where a TUAV will have a probability of being shot down within this area. When a TUAV is shot down, another TUAV will be prepared and launched to the current MTI or to respond to additional MTI data. On the other hand, a functioning TUAV proceeds to location of current MTI and declares whether a target is present or not after reviewing the on-board sensor information. Then, if there are no additional MTIs that need to be developed, the TUAV returns to its Launch & Recovery (L/R) site and waits for new MTIs.

With our swarm system, two TUAVs are launched together to perform this mission. Once the MTI item is transferred from a TOC to a GCS, two TUAVs are prepared for a mission and move to the mission area. For our study the CID process is modeled in the following way: Given that each MTI is a target, once TUAV 1 (or TUAV 2) declares a target is present, this declaration result of TUAV 1 (or TUAV 2) is transferred to the neighboring TUAV 2 (or TUAV 1). On receiving the information, the TUAV 2 (or TUAV 1) stops its discrimination process. Finally, the object is declared (labeled) as an enemy by our fusion algorithm. If TUAV 1 finishes reviewing the

information on the ROI from its onboard sensor earlier than TUAV 2 and does not declare a target is present, the declaration result of TUAV 1 is transferred to TUAV 2 and TUAV 2 continues the discrimination process. If TUAV 2 declares a target is present, our fusion rule returns a target is present in the ROI. If both TUAVs fail to declare the MTI as a target, our fusion algorithm returns no target present in the ROI. In either case, both TUAVs either return to their L/R site or respond to additional MTI data.

Either or both TUAVs can be shot down by the antiaircraft weapon system of an enemy while executing a mission. If one TUAV is shot down in a swarm, the remaining TUAV continues its mission alone until a fresh TUAV is ready. If both TUAVs are shot down, two fresh TUAVs are prepared one by one. As soon as the first TUAV is ready it is launched and performs its mission alone until the second TUAV is ready and launched.

Multiple TUAVs fly in formation in response to each MTI item. In a swarm, one is a leader TUAV and another is a follower TUAV. Therefore the flight speed and position of a follower TUAV depend only on those of a leader TUAV. Figure 3.1 illustrates multiple TUAVs coordinating to discriminate an object.

Figure 3.1 Cooperative UAVs Discriminating an Object

Collision avoidance between TUAVs is not an issue in this research. An efficient CID strategy is to obtain a correct CID call (in our case enemy) in a minimum time by cooperating and coordinating with other TUAVs. Because cooperation can be achieved by communication with other TUAVs, we assume that TUAVs in a swarm communicate with each other for cooperation while performing discriminating tasks.

We assume that each TUAV is provided with the following equipment to enable it to perform ATR: wireless communication capability for sending and receiving information from other TUAVs and the ground station, one image sensor capable of capturing snapshots of the area over which the TUAV flies, a global positioning system (GPS) that returns the 3-d coordinates of the TUAV's current position, image processing software that enables the TUAV to discriminate objects obtained by its image sensors as

a potential target. In a swarm system, each TUAV performs its mission in formation. However, the declaration of a TUAV depends only on its individual onboard sensor information.

In reality, a decision maker at a Brigade TOC has many options to further develop a MTI item. However, we consider only one option, TUAV tasking, is available to him to simplify this CID model and focus on the performance of a swarm system. In addition, though four TUAVs are typically available at the level of Brigade, there is no limitation on number of TUAVs available in our model. Our model also does not consider times required to upload and download information on a MTI or communication problems between TUAVs.

To perform fusion, Boolean logic is used in this research. Though it is easy to implement, Robinson and Aboutalib [24] show that Boolean fusion for decision labels is suboptimal for two or more sensors when each sensor is optimized independently. However, the assumption of independence provides us with a reasonable estimate of system performance (that is also easily implemented in our model) using Boolean fusion for decision labels.

3.2 Simulation Phases

With our given conceptual model of the CID process, there are many different ways to incorporate the objects of interest in a discrete event simulation model. In our CID model, a Moving Target Indicator (MTI) is defined as an entity. A MTI represents a radar presentation which shows only targets which are in motion. Signals from stationary targets are subtracted out of the return signal by the output of a suitable memory circuit.

MTIs are created one at a time with a selected random amount of time between each and are later randomly placed within the defined ROI. A TUAV is modeled as a resource with an unlimited number available. However, only one TUAV can be in active in the system for the single TUAV system, while up to two TUAVs can be active in the swarm system.

Figure 3.2 represents the entire model from creating objects to the CID decision. The main flow consists of several sub models which represents the sub phases and actions occurring in each.

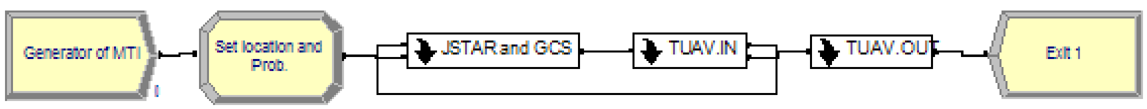

Figure 3.2 Entire Simulation Model

3.2.1 The ROI

The ROI is modeled as the area bounded by a half-circle of radius 50km. The area within this ROI is populated by stationary non-threatening enemies and threats. The locations (xx, yy) of targets are initially unknown. As discussed previously, there is one target placed in the ROI for each MTI. Targets are placed by randomly selecting a distance between 10km and 50km form the center of the ROI and then randomly selecting an angle between zero and pi radians. Figure 3.3 shows a notional ROI with an example target placed.

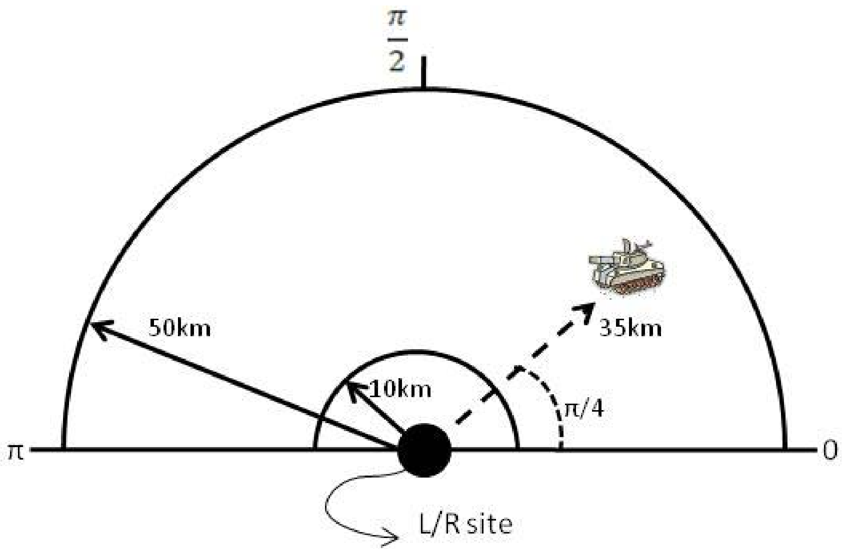

Figure 3.3 Notional ROI with a target

Threats have anti-craft capabilities, such as surface-to-air missiles (SAMs) in each cell. The threat is capable of destroying TUAVs with a kill probability by a random draw (UNIF (0, 1)). The detail will be explained later. Figure 3.3 illustrates attributes assigned for each MTI to position objects within the ROI before proceeding to the next sub model.

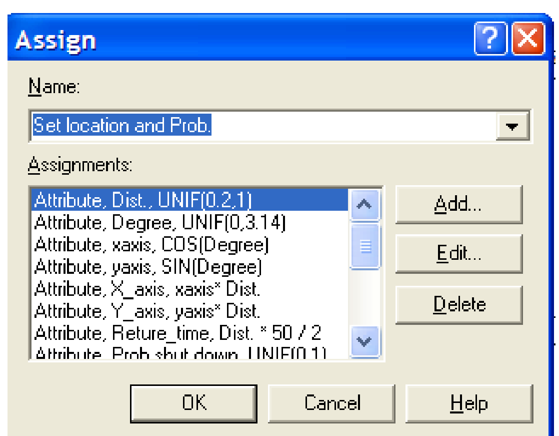

Figure 3.4 Object Allocations for Environment

3.2.2 JSTARs to GCS

Once a ROI is established, as discussed above, each MTI proceeds to be developed through a TUAV tasking to obtain information on its location which is routed to a GCS. The important logic in this phase involves computing the amount of time (T_i) for a TUAV moving from one position to the place where the i^{th} object is located.

Let (*xx, yy*) be a set of *x* and *y* coordinates where an on-board sensor begins a scan to discriminate a target. These coordinates are defined to be three kilometers (fixed) away from the location of a target passed as an MTI. The three kilometers (a survivable standoff range) represents a safe distance that a TUAV has to keep from a target to prevent loss of TUAVs. Consider

$$xx = aa \times \lambda_i + (1 - \lambda_i) \times cc_i$$
$$yy = bb \times \lambda_i + (1 - \lambda_i) \times dd_i \qquad (3.1)$$

where λ_i is defined as:

$$\lambda_i = \frac{3(km)}{50(km) \times \sqrt{(cc - aa)^2 + (dd - bb)^2}}, \qquad (\lambda \in \text{R and } 0 \le \lambda \le 1)$$

and (*aa, bb*) is a set of *x* and *y* coordinate representing a current position of a TUAV and (cc_i, dd_i) is a set of x and y coordinate implying a location of the i^{th} target.

Therefore, a travel time (T_i) of a TUAV for discriminating the i^{th} object can be expressed as:

$$T_i = \sqrt{(xx - aa)^2 + (yy - bb)^2} \times 50(km) \div 2\left({}^{km}/_{min}\right) \qquad (3.2)$$

The distance from (*aa, bb*) to (*xx, yy*) in our ROI is multiplied by 50km to compute a real distance, then it is divided by 2km/min implying an average flight speed of a TUAV to calculate the time (T_i).

The Decision time is the amount of time it takes our ATR system to review information from a sensor on board and make a declaration for an MTI. For our single TUAV system the decision time is uniformly distributed from one to five minutes, while for our swarm system with two TUAVs active, we use the joint distributions (1 + 4 × BETA(1.03, 1.29) min for system and 2, 0.59 + GAMM(0.713, 2.85)min for system 3) developed using another Arena model. To come up with this joint distribution, two hundred decision times were first simulated and collected and then processed using the Arena input analyzer to fit a theoretical distribution function to the data. Figure 3.4 illustrates the sub model for collecting decision times to compute the joint distribution.

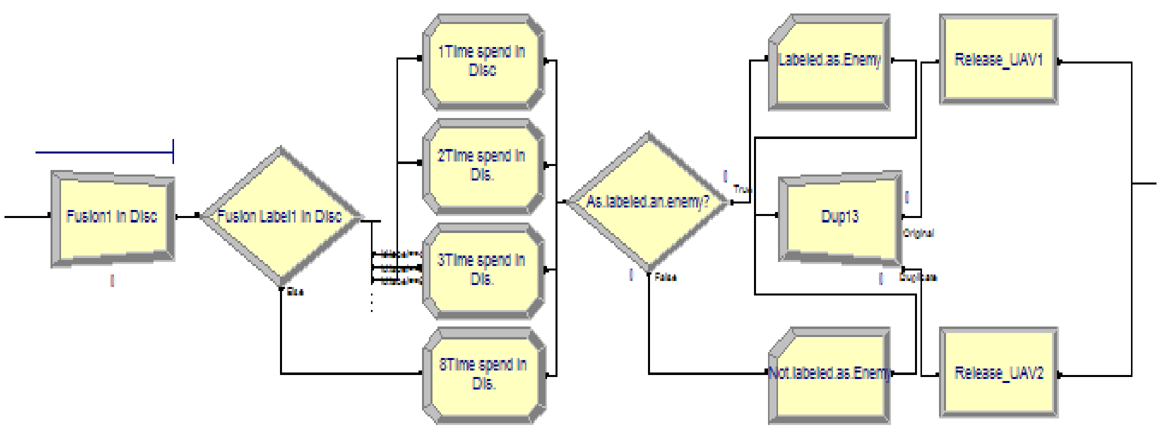

Figure 3.5 Sub model for collecting decision times

For example, if both TUAVs declare a target is present in the simulated ROI, the declarations are saved in the “id.label” as an attribute and the event is defined as Type 4 (used for routing later in model and statistic collection). Then we store the minimum of the two TUAV times for making a target declaration. This follows the logic for our fusion rule where we only require one TUAV declaration to make a decision. The minimum

time in this case is considered the decision time for our swarm system. On the other hand, if two TUAVs declare a target is not present, the maximum time for a declaration with each TUAV is used. The maximum time in this case is considered the decision time of our swarmed system. We use the various decision times as described in coming up with our joint distribution.

3.2.3 TUAV-IN

Once an MTI item is allocated a TUAV (or TUAV swarm), a TUAV moves to the place where the target is located. It takes the amount of time specified in the “TUAV to GCS” sub model. A TUAV first attempts to execute its mission while remaining within its survivable standoff range. However, a TUAV might be restricted in its execution due to dust, cloud, camouflage, and etc. To deal with this situation in our model, we require a TUAV (or TUAV swarm) to proceed beyond its standoff range to perform discrimination a small percentage of the time. Based on [21] we use a fixed probability of 92.5% for successful discrimination and transmission of target information back to the GCS outside of a 3km standoff range. If a TUAV is unable to perform discrimination outside the standoff range (7.5% of the time). The TUAV moves into the standoff range and toward the MTI location a random distance (UNIF(0.5, 1)km) which is expressed as “extra moving distance” in Equation 3.4. While within the standoff range, a TUAV has a 50% probability of being shot down by enemy air defense systems. If shot down, another TUAV is prepared and launched to continue the mission. Otherwise the TUAV continues the CID process by making a declaration and continues back to the L/R point or to another MTI location. Similar logic is used for our swarm system, with separate random

draws taken to determine if one or both TUAVs can perform their mission outside the standoff range and separate draws for survivability if one or both are required to move into the standoff range.

When a TUAV is needed to perform inside of the standoff range, an additional travel time (T_i') of a TUAV for discriminating an i^{th} object can be calculated as follow: Let (*xx*, *yy*) be a set of *x* and *y* coordinate that an on-board sensor of a TUAV begins scanning to discriminate a target after additional moving.

$$xx = aa \times \lambda + (1 - \lambda) \times cc$$

$$yy = bb \times \lambda + (1 - \lambda) \times dd \tag{3.3}$$

where (*aa*, *bb*) is a set of *x* and *y* coordinate representing a current position of a TUAV (i.e., the position that a TUAV is supposed to execute discrimination before deciding to move toward a target more) and (*cc*, *dd*) is a set of *x* and *y* coordinate implying a location of a target. the λ is defined as,

$$\lambda = \frac{3(km) - extra\ moving\ distance(km)}{50(km) \times \sqrt{(cc - aa)^2 + (dd - bb)^2}}, \quad (\lambda \in \mathrm{R} \text{ and } 0 \leq \lambda \leq 1)$$

Therefore, an additional travel time is calculated as,

$$T_i' = \sqrt{(xx - aa)^2 + (yy - bb)^2} \times 50(km) \div 2({}^{km}/_{min}) \tag{3.4}$$

To decide success or failure of the discrimination, our simulation compares a prior TPR (shown in Table 3.1 as P_{TP}) in CM (or a posterior TPR in case of TUAV swarm) with a random number representing the probability of an object being discriminated correctly. For example, if a posterior TPR of a TUAV swarm is 0.9 and the random number is 0.46, the system correctly declares the object a target. However, the system fails to discriminate the target if the random number is greater than the TPR.

Table 3.1 summarizes the probability estimates associated with horizontal analysis of each row, and the vertical analysis metrics in terms of the confusion matrix cells, CM (row, col). For our system we are only interested in the upper left cell of this table since we only model a single class (all objects are targets) and are interested only in the P_{TP} (in our case computed as all objects declared targets divided by all objects).

Table 3.1 Typical Performance Measures Associated with the Confusion Matrix Cells, CM (row, col) [11]

Classifier "Labels"

		"Target" | declaration	*"Friend" | declaration*	*"Non-declaration"*
True Classes	Target	$P_{TP} = \frac{CM(1,1)}{CM(1,1) + CM(1,2)}$	$P_{FN} = \frac{CM(1,2)}{CM(1,1) + CM(1,2)}$ $P_{FN} = 1 - P_{TP}$	$P_{UT} = \frac{CM(1,3)}{CM(1,4)}$
	Friend	$P_{FP} = \frac{CM(2,1)}{CM(2,1) + CM(2,2)}$	$P_{TN} = \frac{CM(2,2)}{CM(2,1) + CM(2,2)}$ $P_{TN} = 1 - P_{FP}$	$P_{UF} = \frac{CM(2,3)}{CM(2,4)}$
Other metrics		$E_{CR} = \frac{P_F P_{FP}}{P_F P_{FP} + P_T P_{TP}}$	$E_{NC} = \frac{P_T P_{FN}}{P_F P_{TN} + P_T P_{FN}}$	$P_{REJ} = P_T P_{UT} + P_F P_{UF}$ $P_{Dec} = 1 - P_{REJ}$

3.2.3.1 Fusion Process for Computing the Posterior TPR

A TUAV swarm makes a CID decision through use of a Boolean fusion rule (logical OR). When one of UAVs in a swarm (or both) declares an enemy is present, the swarm system finally returns a label of enemy. Figure 3.4 presents the Arena model developed with this fusion logic used to generate the TPR for our swarm system.

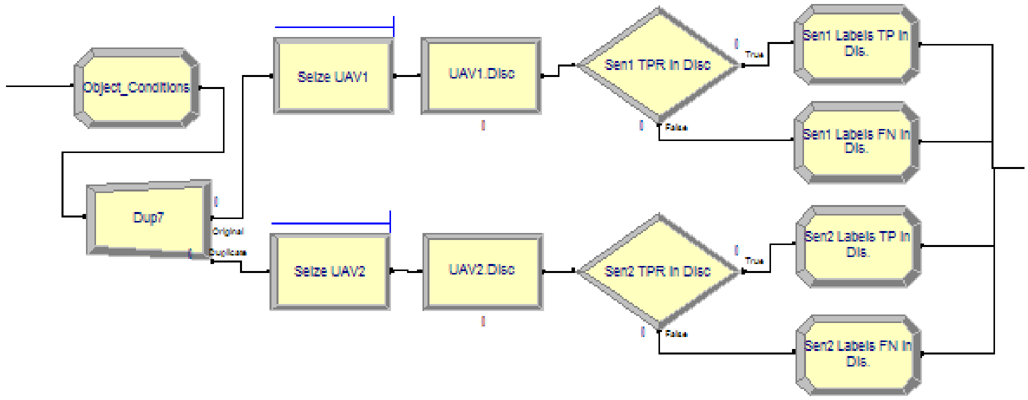

Figure 3.6 Fusion Process in Discrimination

The Boolean logical OR rule is used to combine the output labels from our two TUAV sensors. This rule returns a target for the simulated system if either or both TUAVs conclude an object under investigation is a target. With two sensors fused, $2^2 = 4$ different sensor labels are generated for any given assessment of a target. For example, the following labels of the fusion can be possible: both TUAV 1 and TUAV 2 declare a target is present (defined as case 4 in the simulation model for routing), TUAV 1 declares a target is present while TUAV 2 does not (defined as case 6), TUAV 2 declares a target is present while TUAV 1 does not (defined as case 5), or both TUAVs declare an target is not present (defined as case 7). Therefore, successful declaration of a target where at least one of TUAVs correctly discriminates a target can be represented by 4, 5, and 6 as the output fusion process. If it is labeled as 7, the discrimination process has failed for that object.

3.2.4 TUAV-OUT

After completing its mission, a TUAV (or TUAVs) has three options. One is to return its L/R site and to wait for the arrival of a fresh MTI (i.e., it does not land but flies over the site) when there is no MTI item waiting to be developed. However, if a fresh MTI item arrives at a TUAV GCS before a TUAV reaches the L/R site, a TUAV is redirected from the current position (defined as (*aa, bb*) in our map) to the new ROI (defined as (*cc, dd*)) and performs a new task. If there are any MTIs waiting to be developed after processing the current MTI, a TUAV is immediately redirected to execute new mission. We use a FIFO rule here to deal with which MTI item is first served among MTIs waiting to be developed. If there are any undeveloped MTIs, a TUAV heads to the first one received.

3.3 Variables and attributes

In this section the attributes and variables used throughout the model and in collecting statistics are listed and explained briefly in Table 3.2. These attributes and variables are used as part of the logic throughout the simulation model

Table 3.2 Variables and Attributes in the model

Dist.	Distance from a L/R site of a TUAV to the position of a TUAV beginning its discrimination process
Degree	Centering around a L/R site, an angle of the position of a TUAV beginning its discrimination process
Prob.swarm.shot.down	Probability of either or both TUAVs in a swarm being shot down by enemy air defense systems while executing a mission within its survivable standoff range
Prob.TUAV1.shot.down	Probability of TUAV1 being shot down while executing a mission alone within its survivable standoff range
Prob.TUAV1.shot.down	Probability of TUAV2 being shot down while executing a mission alone within its survivable standoff range
Prob.discriminated. correctly	Probability of an object being discriminated correctly
1Prob.Object.discriminated .inside	Probability of an object being discriminated by TUAV1 inside the standoff range
2Prob.Object.discriminated .inside	Probability of an object being discriminated by TUAV2 inside the standoff range
Decide.time.swarm	Decision time (min) of a swarm system for declaring an object
Decide.time.TUAV1	Decision time (min) of TUAV1 for declaring an object,
Decide.time.TUAV2	Decision time (min) of TUAV2 for declaring an object,
TPR.of.swarm	True Positive Rate of a swarm system when two TUAVs perform discrimination
TPR.of.TUAV1	True Positive Rate of TUAV1 when TUAV1 performs discrimination alone in a swarm system
TPR.of.TUAV2	True Positive Rate of TUAV2 when TUAV1 performs discrimination alone in a swarm system
Prep.time.TUAV1	Time to prepare and launch TUAV1
Prep.time.TUAV2	Time to prepare and launch TUAV2
More.travel.TUAV1	Additional distance in our map that TUAV1 has to move to discriminate an object inside the standoff range
More.travel.TUAV2	Additional distance in our map that TUAV2 has to move to discriminate an object inside the standoff range
aa	*x*-coordinate of the current position of a TUAV in a single TUAV system or a leader TUAV in a swarm system
bb	*y*-coordinate of the current position of a TUAV
Num.of.TUAVs	Number of TUAVs in the simulation
Num.TUAVs.shot.down	Number of TUAVs shot down
Total.decision.time	Total decision time of a system until the simulation is terminated
Total.TUAVs.Prep.time	Total time that a GCS spend to prepare and launch TUAVs
id.label	Decision label of a TUAV in discrimination process.

3.4 Verification and Validation

In this section, verification and validation of the simulation model are discussed. Verification is a process that is used to check if a simulation model is coded correctly or logic in the model is correct. Validation is the process of establishing a high level of assurance that a simulation model matches the real system.

The simulation model can be verified by the animation feature of Arena. Whenever a module for building each process of CID is added, our simulation model is run to check if the flow of entity is appropriate or not.

Currently, no UAV swarm concept is being employed based on the finding in this region. Therefore, the face validity is used for validation of our simulation model. Our results of model are reasonable with expected performances for the hypothesized system

3.8. Conclusion

This chapter focused on description and assumptions of the simulation model, concepts of building a simulation model and application of steps for making our simulation model reasonable. The specific variables and attributes for our research were also described. Results and analysis from our model are discussed in the next chapter.

IV. Analysis and Results

General

This chapter focuses on model results and analysis. In the first section, we present the factors used and output data obtained in our model, and the appropriate replication length and number also are discussed. The following include comparisons between different competing systems on the various performance measures and the analysis of responses from this simulation model.

4.1 Measure of Effectiveness

Measures of Effectiveness (MOE) in various fields of military require some kind of quantification. Number of targets detected, survivability score, aircraft availability and accident rates, and many other measures serve to reduce a large number of data into meaningful information. Quantitative methods are used to analyze and explain actions or outputs to a decision maker such as the commander of a Brigade.

MOEs should be selected and interpreted with care, because MOEs that appropriately distill and precisely reflect reality help decision makers make informed, timely decisions. If measures are poorly selected or wrongly interpreted, the collection and analysis of the MOE may waste time and effort [25].

In this research, the outputs we captured are the accumulated accuracy, the number of TUAVs shot down, mean of simulated mission time, mean of decision time per a MTI, and total time for TUAV preparation.

Each scenario is run for 30 replications. This number of replications was selected because 30 replications are generally enough to meet Central Limit Theorem condition for independent and identically-distributed random variables and give us a reasonable half width (for each MOE plus or minus 5%).

4.2 Simulation Results

In this section we present the simulation results of the systems using the following three different configurations.

- A high-value sensor which has a high-level TPR (called system 1)
- Two low-value sensors which has a low-level TPR (system 2)
- Two middle-value sensors which has a middle-level TPR (system 3)

Table 4.1 Specification of a sensor used in each system

<table>
<tr><th>Level</th><th>TPRs</th><th>Decision time</th><th colspan="2">Prob. of a TUAV successfully discriminating target inside of the stand-off range</th></tr>
<tr><td>High</td><td>UNIF(0.85,0.97)
Improved by 30%</td><td>UNIF(0.91,4.91)
Improved by 3%</td><td>0.938875
Improved by 1.5%</td><td rowspan="3">Improvement based on the value of low-level</td></tr>
<tr><td>Middle</td><td>UNIF(0.71,0.83)
Improved by 10%</td><td>UNIF(0.97,4.97)
Improved by 1%</td><td>0.929625
Improved by 0.5%</td></tr>
<tr><td>Low</td><td>UNIF(0.64,0.76)</td><td>UNIF(1,5)</td><td>0.925</td></tr>
</table>

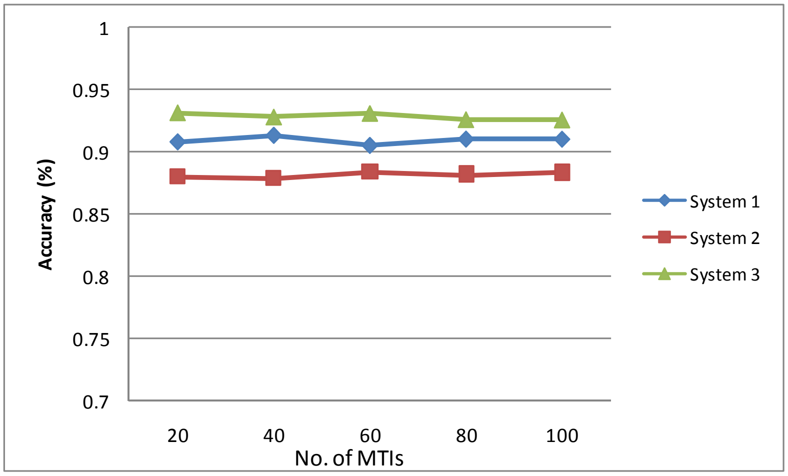

Figure 4.1 Accuracy of the systems as a function of No. of MTIs

To assess the performances of the system using one of three configurations described above, we simulated each system in the environments with 20, 40, 60, 80, and 100 targets (labeled as MTIs in our figures). For all the simulation runs in this paper, the homogeneous targets are randomly assigned to the ROIs while a system executes its mission. We synchronize use of the same random number streams for the same purpose when simulating each of our systems, therefore, the location of targets and the threats level of targets are all the same for each configuration.

From Figure 4.1 we can see that the System 3 out-performs the others in terms of the accumulated accuracy of a system. The performance of System 3 with two middle-value sensors fares better than the system with two low-value sensors and the system one high-value sensor. Although the TPR of the sensor used in System 3 is less than that of the sensor in System 1, the performance of System 3 is more successful than that of System 1 because of the increased TPR with fusion of information in our swarm system.

We looked at additional simulation outputs to study the performances of these systems for the same ROIs. Figure 4.2 shows loss of TUAVs and preparation time for fresh TUAVs over the same range of targets.

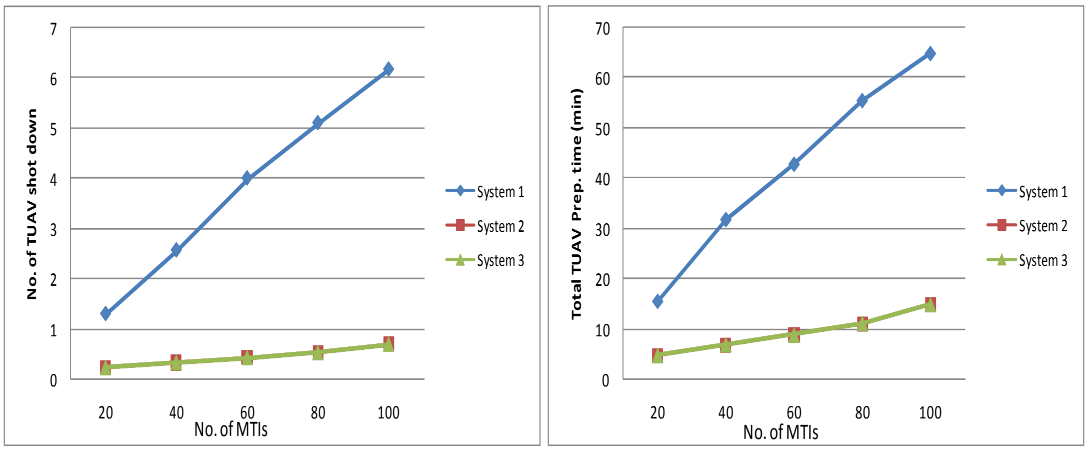

Figure 4.2 Number of TUAVs shot down and TUAV preparation time as a function of No. of MTIs

These values give a good indication of the survival rate of a single TUAV (System 1) versus use of a swarm system (System 2 and 3). It is obvious that our cooperative method provides a significant improvement in the number of TUAVs shot down. As discussed before, a TUAV can be shot down when it performs discrimination inside of the standoff range. If it executes its mission outside of the range, the TUAV is secure from any threats. In addition, if at least one TUAV in the swarm can execute its task outside this range, our cooperative algorithm does not allow the remaining TUAV to move inside of the range for discrimination. It only allows TUAVs to move inside the standoff range when both TUAVs fail to perform discrimination outside of the range.

This is why the numbers of TUAVs shot down with one of our swarm systems are significantly less than that number for System 1, the single TUAV system. The pattern of the two plots in Figure 4.2 looks similar to each other. It does make sense because the smaller loss of TUAVs, the less preparation time for fresh TUAVs, however, there is little difference between the performances of the two swarm systems for either plot in Figure 4.2. This indicates that this MOE is more dependent on our cooperative algorithm with a swarm system than the increased TPR of System 3 over System 2.

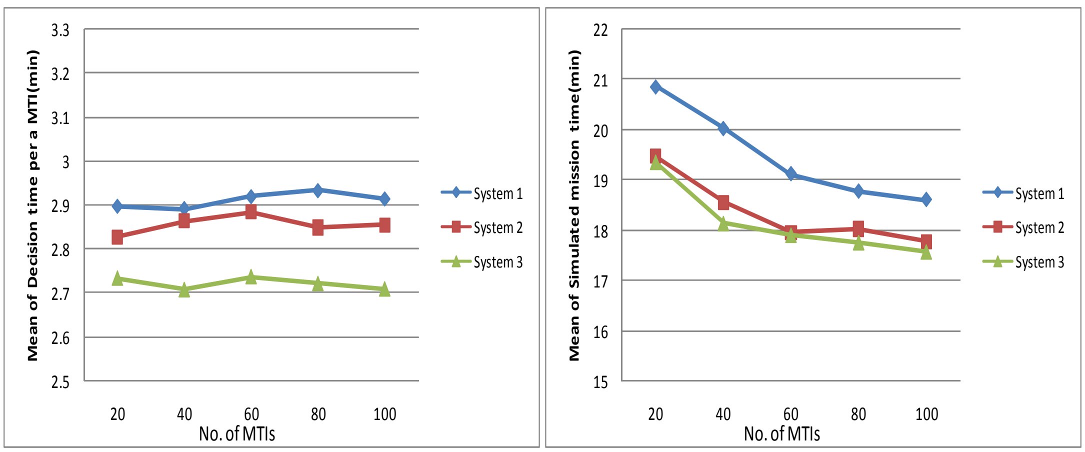

Figure 4.3 Mean of Decision and Simulated mission time as a function of No. of MTIs

The left plot in Figure 4.3 shows mean of decision time representing the mean time that a system spends collecting data and making a declaration for an object. The right plot shows mean of simulated mission time. The performances of the proposed fusion algorithm (System 2 and 3) were compared to that of the system using one TUAV. In our fusion algorithm, successful declaration of a target is defined as the case where at least one TUAV correctly discriminates a target. We also modeled the single TUAV

decision time as being slightly improved over the two swarm systems. Therefore, we expected to see some decrease in the swarm system performance for this measure. As we can see from Figure 4.3, the performances of the swarm systems are slightly better than that of the single TUAV system. This is due to once again to our fusion rule. Once one of the TUAVs declares a target is present, the other TUAV does not spend time on the same object leading to a decrease in decision time. In addition since we assumed the middle-level sensor used in the System 3 is slightly improved based on the low-level, the performance of System 3 is better than that of System 2.

Our mean of simulated mission time (Figure 4.3) depends strongly on TUAVs preparation time, travel time, inter-arrival time between MTIs, and decision time. The simulated mission times of the swarm systems are less than that of the System 1. As presented before, the total TUAVs preparation time and decision time of the swarm system are less than those of the System 1. In addition, since the locations of targets and the flight speed of TUAVs in our simulation are all the same while the TUAVs of each system perform its mission, the total travel time of each system differs little from each other. This is why the swarm systems show better performance in terms of shorter mean of simulated mission time. As the number of MTIs increase, mean of simulated mission time of three systems tends to decrease. At the beginning of these simulations, an inter-arrival time between MTIs strongly affects the simulated mission time because the longer an inter-arrival time between MTIs, the bigger the simulated mission time. However, as the number of MTIs increase more of the time there will be MTIs waiting to be developed. In such a case the inter-arrival time does not affect the simulated mission time anymore and the travel times of TUAVs decrease because TUAVs directly move to the

next MTI without spending time going back and forth to L/R point. This is why the mean of simulated mission time decreases as the number of MTIs increase.

4.3 Comparison of Competing Systems

In this section statistical analysis is performed to answer the question of whether or not these measures represent a statistically significant difference in performance of the three systems. One approach is to compare the confidence intervals for a pair of means and unless they overlap we can say the difference between these system means is statistically significant. This is an informal test and we set up a hypothesis to provide us a decision based on a chosen confidence level in order to quantify how certain we are of the difference [2:164].

The paired t-test is a common method to compare alternatives of real systems. The statistic for this test is the difference between the two alternatives for each replication. The null hypothesis is that the mean of the differences is zero. This approach does not require equal variances and independence between systems, but the sample size should be equal.

Because the output from a simulation is a random variable, the precision of the results from the simulation will be decided by the variance of the output. One statistical technique to reduce such a variance is the use of Common Random Numbers (CRN) along with the paired t-test. The idea of using CRN is to ensure that alternative configurations of a model are different only due to those configurations and not due to different random conditions used in the model, so the use of an exclusive random number

stream for each place in the simulation where a random variate draw occurs is advised [2:169].

Three different systems are used in this study. All requirements, such as dedicated random number streams and starting replications for each system with the same random number, related to getting the most form using CRN are incorporated in our simulation. These different system configurations are examined in terms of accuracy, number of TUAVs shot down, TUAV preparation time, decision time, and simulated mission time of the systems. The following discussion presents paired t-test results comparing performance of the single TUAV and the swarm systems for sets of 20, 60, and 100 targets (MTIs). All confidence intervals used are two-tailed at a 95% level of confidence and all p-values are two-tailed.

The first paired t-test (Table 4.2) was performed to determine if the means of the difference between these systems is zero in terms of accuracy.

Table 4.2 Paired t-test for Accuracy (%)

MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	0.90833	0.07081	0.01293
Sys 2	30	0.88000	0.07944	0.01450
Diff.	30	0.02833	0.05972	0.01090
95% CI		0.00603		0.05063
P-value		0.01456		

MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	0.90833	0.07081	0.01293
Sys 3	30	0.93167	0.06757	0.01234
Diff.	30	-0.02333	0.05529	0.01010
95% CI		-0.04398		-0.00269
P-value		0.02812		

MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	0.90556	0.04160	0.00759
Sys 2	30	0.88389	0.04844	0.00884
Diff.	30	0.02069	0.04424	0.00822
95% CI		0.00386		0.03752
P-value		0.01120		

MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	0.90556	0.04160	0.00759
Sys 3	30	0.93111	0.03178	0.00580
Diff.	30	-0.02556	0.03681	0.00672
95% CI		-0.03930		-0.01181
P-value		0.00068		

MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	0.91033	0.02977	0.00543
Sys 2	30	0.88700	0.03583	0.00654
Diff.	30	0.02333	0.03871	0.00707
95% CI		0.00888		0.03779
P-value		0.00256		

MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	0.91033	0.02977	0.00543
Sys 3	30	0.92600	0.02513	0.00459
Diff.	30	-0.01567	0.02837	0.00518
95% CI		-0.02626		-0.00507
P-value		0.00517		

In the case of the comparison of System 1 (single TUAV) and System 2, the means of the difference are significantly greater than zero, none of the confidence intervals contain zero, and all the P-values are less than 0.05, providing evidence that System 1 shows better performance than System 2. On the other hand, for System 1 and System 3 all the means of differences are less than zero, none of the confidence intervals contain zero, and all the P-values are less than 0.05. It indicates that the accuracy of System 3 is higher than that of the System 1. However, the differences range from only about one to four percent which may not be practically significant, but would need to be researched further.

The second paired t-test (Table 4.3) was used to test the null hypothesis that the numbers of TUAVs shot down with the single TUAV and each swarm system are statistically the same. Here all confidence intervals lie above zero indicating that the number of TUAVs shot down with System 1 is statistically larger either swarm system. The results indicate that in terms of survival rate the performance of a swarm system is better than that of a single TUAV system.

Table 4.3 Paired t-test for Number of TUAVs shot down

No. of TUAVs shot down				
MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	1.30000	1.20773	0.22050
Sys 2	30	0.23333	0.67891	0.12395
Diff.	30	1.06667	1.25762	0.22961
95% CI		0.59706		1.53627
P-value		0.00007		

No. of TUAVs shot down				
MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	1.30000	1.20773	0.22050
Sys 3	30	0.23333	0.67891	0.12395
Diff.	30	1.06667	1.25762	0.22961
95% CI		0.59706		1.53627
P-value		0.00007		

No. of TUAVs shot down				
MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	4.00000	2.01717	0.36828
Sys 2	30	0.43333	0.81720	0.14920
Diff.	30	3.56667	2.22344	0.40594
95% CI		2.73642		4.39691
P-value		0.00000		

No. of TUAVs shot down				
MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	4.00000	2.01717	0.36828
Sys 3	30	0.43333	0.81720	0.14920
Diff.	30	3.56667	2.22344	0.40594
95% CI		2.73642		4.39691
P-value		0.00000		

No. of TUAVs shot down				
MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	6.16667	2.54725	0.46506
Sys 2	30	0.70000	1.31700	0.24045
Diff.	30	5.46667	2.51524	0.45922
95% CI		4.52746		6.40587
P-value		0.00000		

No. of TUAVs shot down				
MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	6.16667	2.54725	0.46506
Sys 3	30	0.70000	1.31700	0.24045
Diff.	30	5.46667	2.51524	0.45922
95% CI		4.52746		6.40587
P-value		0.00000		

The third paired t-test (Table 4.4) was performed to test if there is difference in the performance representing the TUAV preparation time of the swarm systems and the single TUAV system. As shown in this table, none of the confidence intervals contain zero and all the P-values are below 0.05, so the difference is statistically significant. Because the smaller value in this measure implies the better performance, we can say that the swarm systems lead to a decrease in TUAV preparation time.

Table 4.4 Paired t-test for TUAV preparation time (minutes)

TUAVs Prep. time				
MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	15.46600	20.39687	3.72394
Sys 2	30	4.71390	13.97316	2.55114
Diff.	30	10.75210	23.06731	4.21150
95% CI		2.13862		19.36558
P-value		0.01620		

TUAVs Prep. time				
MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	15.46600	20.39687	3.72394
Sys 3	30	4.71390	13.97316	2.55114
Diff.	30	10.75210	23.06731	4.21150
95% CI		2.13862		19.36558
P-value		0.01620		

TUAVs Prep. time				
MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	42.78557	34.08991	6.22394
Sys 2	30	8.81667	16.98095	3.10028
Diff.	30	33.96890	38.99293	7.11910
95% CI		19.40870		48.52910
P-value		0.00005		

TUAVs Prep. time				
MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	42.78557	34.08991	6.22394
Sys 3	30	8.81667	16.98095	3.10028
Diff.	30	33.96890	38.99293	7.11910
95% CI		19.40870		48.52910
P-value		0.00005		

TUAVs Prep. time				
MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	64.85667	36.05568	6.58284
Sys 2	30	14.96887	28.01269	5.11439
Diff.	30	49.88780	38.27825	6.98862
95% CI		35.59447		64.18113
P-value		0.00000		

TUAVs Prep. time				
MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	64.85667	36.05568	6.58284
Sys 3	30	14.96887	28.01269	5.11439
Diff.	30	49.88780	38.27825	6.98862
95% CI		35.59447		64.18113
P-value		0.00000		

The fourth set of paired t-tests examining the difference of mean of decision time between the single and swarm system are shown in Table 4.5. For the smallest number of targets (MTIs = 20), there is no statistical difference in the mean of decision time between the systems because the confidence intervals contain zero and the P-values are much larger than 0.05. However, as the number of targets increase (which clearly

increase mission time), the difference between systems grows, with a significant difference between System 1 and 3 at 60 targets, and significant difference between the single TUAV and both swarm systems at 100 targets.

Table 4.5 Paired t-test for mean of decision time (minutes)

MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	2.899352	0.297227	0.055194
Sys 2	30	2.827463	0.228567	0.04173
Diff.	30	0.07004	0.375886	0.068627
95% CI		-0.07032		0.21040
P-value			0.31589	

MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	2.899352	0.297227	0.055194
Sys 3	30	2.734633	0.324942	0.059326
Diff.	30	0.16287	0.474003	0.086541
95% CI		-0.01413		0.33987
P-value			0.06991	

MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	2.919843	0.139549	0.025478
Sys 2	30	2.883583	0.151786	0.027712
Diff.	30	0.03626	0.203542	0.037161
95% CI		-0.03974		0.11226
P-value			0.33726	

MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	2.919843	0.139549	0.025478
Sys 3	30	2.737937	0.175466	0.032036
Diff.	30	0.181907	0.208019	0.037979
95% CI		0.10423		0.25958
P-value			0.00005	

MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	2.914603	0.107031	0.019541
Sys 2	30	2.854067	0.112013	0.020451
Diff.	30	0.060537	0.16211	0.029597
95% CI		0.00000		0.12107
P-value			0.04999	

MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	2.914603	0.107031	0.019541
Sys 3	30	2.710083	0.115408	0.02107
Diff.	30	0.20452	0.151809	0.027716
95% CI		0.14783		0.26121
P-value			0.00000	

Finally, the null hypothesis that the mean of the difference in simulated mission time of the swarm system and single TUAV system is zero is tested by a paired t-test. These results are shown in Table 4.6. The difference between System 1 and System 2 is not statistically significant for simulated mission time, while the difference between System 1 and System 3 is statistically significant. However, it is found that the difference between System 1 and System 3 may not be practically significant, because the performance of System 3 has decreased by about 6% compared to the performance of System 1 and the difference can be considered to be not significant in the real world.

Table 4.6 Paired t-test for mean of simulated mission time (minutes)

MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	20.64983	3.209447	0.585962
Sys 2	30	19.4644	2.24118	0.409182
Diff.	30	1.185433	3.913194	0.714448
95% CI		-0.27578		2.64664
P-value		0.10785		

MTIs=20	N	Mean	St. Dev.	SE Mean
Sys 1	30	20.64983	3.209447	0.585962
Sys 3	30	19.34167	2.697191	0.492437
Diff.	30	1.308167	3.088029	0.563794
95% CI		0.15508		2.46126
P-value		0.02756		

MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	18.97897	1.869383	0.341301
Sys 2	30	18.1579	1.475109	0.269317
Diff.	30	0.821067	2.326918	0.424835
95% CI		-0.04782		1.68995
P-value		0.06310		

MTIs=60	N	Mean	St. Dev.	SE Mean
Sys 1	30	18.97897	1.869383	0.341301
Sys 3	30	17.9007	1.345255	0.245609
Diff.	30	1.078267	1.676573	0.306099
95% CI		0.45222		1.70431
P-value		0.00144		

MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	18.3621	1.251194	0.228436
Sys 2	30	17.78377	1.095421	0.199996
Diff.	30	0.578333	1.615134	0.294882
95% CI		-0.02477		1.18143
P-value		0.05952		

MTIs=100	N	Mean	St. Dev.	SE Mean
Sys 1	30	18.3621	1.251194	0.228436
Sys 3	30	17.5714	1.09267	0.199493
Diff.	30	0.7907	1.43563	0.262109
95% CI		0.25463		1.32677
P-value		0.00527		

4.4 Conclusion

In this chapter, statistical analysis on the outputs from our simulation was discussed. First the proper length and number of replications of our simulation model was determined, then the factors which contribute to our model were presented. Finally by using a paired t-test, the performances of the systems having different configuration were analyzed. The following chapter will discuss the conclusions and recommendations.

V. Conclusions and Recommendations

General

This chapter gives a short summary and conclusions of this research, and then recommendations for future research are discussed.

5.1 Summary and Conclusions

The objective of this research was to analyze a TUAV swarm with low-value sensors versus a single UAV with a high-value sensor to investigate the effects of changing defined variables in the CID process. First, we constructed a detailed computer model of the entire CID process with only targets present after making several assumptions, and defining a number of variables, and desired statistics. We defined three different systems (a single TUAV and two different swarm configurations) and performed 30 replications for each. The outputs from these different configurations were captured and five performance measures were evaluated.

In this study, we simulated a CID process using a TUAV swarm for discriminating a target within an unknown region. A key issue to capture swarm behavior of TUAVs is to design logic such that the swarm of TUAVs performs the discrimination mission cooperatively based on information they get. We developed a cooperative fusion algorithm using a Boolean OR rule.

Five measures are evaluated for the comparison of different systems. These measures are accuracy, number of TUAV shot down, TUAV preparation time, mean of

decision time, and mean of simulated mission time. The performance achieved using a single TUAV was compared with the swarm systems. As shown in Table 5.1, the swarm systems are consistently better (across all performance measures). For System 2 we picked the sensor capabilities for the swarm to roughly match the TPR performance of the single TUAV. For System 3 the sensor levels were selected in order for the TPR performance of System 3 to show a modest improvement over System 2.

Table 5.1 System showing better performance in each environment

No. of MTIs	No. of TUAVs shot down	TUAV preparation time (min)	Decision time (min)	Simluation time (min)	Accuracy (%)
20	Swarm	Swarm	No diff.	No diff.	Swarm (System 3)
60	Swarm	Swarm	Swarm (System 3)	Swarm	Swarm (System 3)
100	Swarm	Swarm	Swarm	Swarm	Swarm (System 3)

The results of the statistical tests indicate we can cut down our expenses for purchasing air frames and sensors by employing the swarm system that we proposed because our swarm system shows much better performance than the single TUAV system in terms of number of TUAVs shot down. Besides, we can decrease research and development expenditures for developing sensor capabilities because as we can see in Table 5.1, sending two coordinated TUAVs (our swarm systems) with less complex sensors leads to an equivalent or even better CID call than sending a single TUAV with more sophisticated sensor. Cost is a driving factor for constructing and maintaining a

military system and a decision maker wants to achieve the maximum efficiency at a minimum of effort and cost. Because of the significant reduction in costs with our swarm system from fewer TUAV platform lost to enemy fire in the scenarios examined along with a much lower projected sensor cost, we conclude that our swarm system with fused sensors presents the potential for future employment.

5.2 Recommendations for Future Study

This simulation model can be improved by adding an additional process such as classification and identification as well as including both friendly objects and clutter in each ROI. For people who study ATRs, an entire CID process consists of five processes. These are detection, discrimination, classification, recognition, and identification. By modeling from detection to identification with different object types, we can get more robust measures of system performance in a more realistic operational environment.

Current sensor and classifier fusion texts provide evidence not only to Boolean fusion rules' general use and acceptance but also to their easy implementation. However, as mentioned in Chapter 3, the use of Boolean fusion for decision labels results in suboptimal for more than two sensors when each sensor is optimized independently. Modeling different levels of correlation among fused sensors and exploring other fusion rules may lead to improved system performance.

In addition, by adding and modeling costs for operating the system (i.e., research and development expenditures and expenses for purchasing sensors and air frames, we can get more robust measures related to cost-effectiveness.

Appendix A. Decision times of System 2 for computing

the Joint Distribution of Decision time

Obser.	Decision Time	Obser.	Decision Time	Obser.	Decision Time	Obser.	Decision Time	Obser.	Decision Time
1	2.2741	41	4.0796	81	3.0263	121	2.5115	161	2.12
2	1.3176	42	1.366	82	1.8724	122	1.1572	162	2.9964
3	2.0479	43	2.2961	83	3.1915	123	1.9864	163	3.3975
4	3.0128	44	1.9214	84	3.95	124	1.0782	164	3.5007
5	4.7687	45	4.1515	85	1.7938	125	1.3234	165	3.5475
6	1.8524	46	3.1157	86	3.5648	126	3.6882	166	1.5686
7	2.9912	47	1.2693	87	3.5776	127	3.3462	167	2.8005
8	2.6575	48	1.7961	88	1.4115	128	4.8182	168	1.5516
9	3.8534	49	4.6784	89	2.7369	129	1.6595	169	2.546
10	1.2849	50	4.6402	90	2.2583	130	3.9649	170	1.7544
11	1.019	51	2.5055	91	1.757	131	3.5509	171	2.6032
12	2.8035	52	2.9171	92	2.7755	132	3.4896	172	4.5282
13	2.917	53	3.9767	93	4.0217	133	3.2053	173	1.7274
14	2.4238	54	2.5971	94	3.5783	134	1.1893	174	3.1034
15	2.6494	55	4.067	95	1.8514	135	1.6737	175	3.6694
16	1.2517	56	2.2324	96	4.2135	136	4.1399	176	1.1742
17	3.165	57	4.3188	97	4.2689	137	4.8479	177	3.1843
18	2.1216	58	4.0718	98	2.9485	138	1.4924	178	1.7444
19	1.3259	59	2.2072	99	4.8257	139	1.0542	179	3.7596
20	2.827	60	4.004	100	2.0861	140	3.0849	180	2.0802
21	3.2456	61	2.522	101	1.8054	141	4.8184	181	3.9897
22	3.5875	62	1.0495	102	3.0221	142	4.4169	182	2.2492
23	3.1902	63	4.92	103	1.0112	143	2.4975	183	2.1124
24	3.8602	64	4.1507	104	4.3401	144	4.008	184	2.1551
25	3.0345	65	3.2836	105	1.2508	145	2.9522	185	4.295
26	1.9815	66	1.6889	106	2.9335	146	2.2435	186	3.1539
27	4.773	67	1.7597	107	1.5967	147	4.4196	187	1.9713
28	1.8357	68	3.9707	108	1.0571	148	1.3722	188	1.7656
29	3.4543	69	1.6218	109	1.1236	149	1.2961	189	2.1627
30	4.2258	70	2.4886	110	2.146	150	3.4396	190	1.5564
31	4.0128	71	1.2417	111	4.6991	151	3.5975	191	1.9686
32	2.3925	72	2.2004	112	4.1527	152	3.1413	192	2.4398
33	1.7588	73	2.6371	113	1.0859	153	3.5084	193	2.6077
34	4.8875	74	3.2283	114	3.3519	154	3.9024	194	3.1387
35	4.769	75	3.0252	115	3.6183	155	3.3662	195	3.8958
36	2.1407	76	3.1724	116	3.2912	156	3.1524	196	3.2427
37	3.7364	77	2.3263	117	4.1124	157	4.4756	197	4.146
38	4.4123	78	1.0959	118	2.9527	158	3.0534	198	1.8907
39	2.271	79	1.8612	119	3.232	159	1.9517	199	3.2574
40	1.5128	80	2.9534	120	2.0684	160	1.8329	200	2.0761

Appendix B. TPRs of System 2 for computing the Joint Distribution of TPR

Obser.	TPR	Obser.	TPR	Obser.	TPR
1	0.91	36	0.95	71	0.92
2	0.92	37	0.94	72	0.93
3	0.89	38	0.95	73	0.93
4	0.86	39	0.89	74	0.89
5	0.99	40	0.93	75	0.93
6	0.92	41	0.92	76	0.9
7	0.84	42	0.87	77	0.89
8	0.93	43	0.97	78	0.94
9	0.91	44	0.9	79	0.86
10	0.93	45	0.92	80	0.93
11	0.89	46	0.9	81	0.94
12	0.92	47	0.9	82	0.95
13	0.96	48	0.88	83	0.93
14	0.92	49	0.94	84	0.92
15	0.93	50	0.92	85	0.92
16	0.92	51	0.9	86	0.9
17	0.93	52	0.95	87	0.92
18	0.95	53	0.86	88	0.9
19	0.95	54	0.97	89	0.89
20	0.87	55	0.95	90	0.95
21	0.95	56	0.94	91	0.98
22	0.92	57	0.9	92	0.9
23	0.89	58	0.91	93	0.91
24	0.92	59	0.91	94	0.87
25	0.93	60	0.93	95	0.87
26	0.9	61	0.93	96	0.92
27	0.94	62	0.91	97	0.91
28	0.92	63	0.88	98	0.91
29	0.88	64	0.92	99	0.86
30	0.83	65	0.86	100	0.94
31	0.92	66	0.88		
32	0.95	67	0.86		
33	0.89	68	0.93		
34	0.9	69	0.85		
35	0.91	70	0.93		

Appendix C. Decision times of System 3 for computing the Joint Distribution of Decision time

Obser.	Decision time	Obser.	Decision time	Obser.	Decision time	Obser.	Decision time	Obser.	Decision time
1	1.478	41	3.9669	81	2.9963	121	2.4815	161	4.5235
2	1.2876	42	3.2752	82	1.8424	122	1.1272	162	2.4344
3	2.0179	43	4.8172	83	2.8733	123	2.3835	163	1.7812
4	2.9828	44	3.5777	84	3.92	124	1.2422	164	3.7953
5	4.7387	45	2.4392	85	1.7638	125	2.5799	165	3.5175
6	1.898	46	1.5849	86	3.5348	126	3.6582	166	2.0262
7	1.1924	47	4.1724	87	3.5476	127	3.2409	167	1.6029
8	2.61	48	1.151	88	1.3815	128	1.8822	168	1.5216
9	3.8234	49	4.6484	89	1.304	129	1.3437	169	2.768
10	4.6018	50	4.6102	90	4.1162	130	2.317	170	1.7244
11	0.98909	51	4.2969	91	2.2829	131	1.8376	171	1.1157
12	2.2611	52	2.8871	92	1.7002	132	2.1187	172	1.8311
13	1.3404	53	4.7796	93	3.9917	133	3.0291	173	4.2117
14	3.465	54	2.5671	94	1.574	134	1.1593	174	1.3262
15	2.6194	55	4.037	95	1.2516	135	1.6437	175	3.6394
16	1.3754	56	1.1851	96	4.1835	136	4.2363	176	2.9495
17	2.776	57	4.2888	97	1.7787	137	4.8179	177	2.2707
18	2.0916	58	3.264	98	2.6487	138	4.5368	178	1.8605
19	1.2959	59	1.299	99	4.7957	139	1.0242	179	3.6795
20	2.797	60	1.6416	100	1.8178	140	1.3523	180	2.802
21	3.2156	61	1.6806	101	1.7754	141	1.7408	181	1.7151
22	3.5575	62	1.1319	102	3.4249	142	2.1068	182	1.6452
23	2.933	63	2.9396	103	1.8717	143	1.4007	183	4.1335
24	4.1267	64	3.3325	104	4.3101	144	2.8815	184	4.4041
25	3.3978	65	4.4178	105	2.7043	145	2.9222	185	1.103
26	2.3609	66	1.6589	106	1.2919	146	2.2135	186	2.8286
27	4.4769	67	2.5695	107	1.5667	147	2.2866	187	1.9413
28	2.5866	68	3.9407	108	1.0271	148	1.268	188	2.3281
29	3.4243	69	1.3441	109	1.0936	149	1.7487	189	3.4004
30	4.1958	70	2.2521	110	2.116	150	1.9476	190	1.5264
31	3.9828	71	1.2117	111	4.6691	151	3.5675	191	4.0938
32	1.0219	72	2.9439	112	3.1724	152	2.7379	192	2.4098
33	1.3266	73	2.6071	113	1.0559	153	1.5587	193	2.5777
34	4.8575	74	1.3198	114	3.3219	154	4.9649	194	3.8708
35	3.4945	75	4.6561	115	2.3209	155	4.1425	195	3.8658
36	2.9028	76	1.6135	116	2.0113	156	3.9895	196	2.8419
37	3.0504	77	2.2963	117	1.021	157	1.6943	197	1.504
38	2.3913	78	1.9079	118	4.9249	158	3.9224	198	1.8607
39	2.1549	79	1.0546	119	3.694	159	1.4385	199	1.2182
40	1.4828	80	2.5334	120	1.4839	160	1.8029	200	2.0775

Appendix D. TPRs of System 3 for computing the Joint Distribution of TPR

Obser.	TPR	Obser.	TPR	Obser.	TPR
1	0.93	36	0.96	71	0.93
2	0.95	37	0.96	72	0.93
3	0.91	38	0.98	73	0.96
4	0.91	39	0.95	74	0.92
5	0.99	40	0.97	75	0.94
6	0.95	41	0.95	76	0.95
7	0.89	42	0.93	77	0.95
8	0.94	43	0.98	78	0.96
9	0.93	44	0.92	79	0.93
10	0.93	45	0.96	80	0.96
11	0.97	46	0.93	81	0.96
12	0.94	47	0.95	82	0.97
13	0.97	48	0.93	83	0.94
14	0.95	49	0.96	84	0.94
15	0.97	50	0.97	85	0.92
16	0.96	51	0.94	86	0.93
17	0.94	52	0.96	87	0.96
18	0.98	53	0.9	88	0.94
19	0.99	54	0.97	89	0.92
20	0.91	55	0.97	90	0.95
21	0.99	56	0.95	91	0.99
22	0.92	57	0.97	92	0.97
23	0.94	58	0.97	93	0.94
24	0.96	59	0.97	94	0.92
25	0.93	60	0.97	95	0.92
26	0.93	61	0.97	96	0.98
27	0.97	62	0.94	97	0.93
28	0.95	63	0.95	98	0.96
29	0.92	64	0.96	99	0.95
30	0.9	65	0.93	100	0.99
31	0.96	66	0.92		
32	0.96	67	0.91		
33	0.94	68	0.95		
34	0.95	69	0.92		
35	0.94	70	0.94		

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14. ABSTRACT
In modern warfare, Tactical Unmanned Aerial Vehicles (TUAVs) are rapidly taking on a leading role in traditional and non-traditional ISR, to include Automatic Target Recognition (ATR). However, additional advancements in processors and sensors on TUAVs are still needed before they can be widely employed as a primary source for positive identification in the Combat Identification (CID) process. Cost is a driving factor for operating an ATR system using multiple TUAVs. The cost of high quality sensors appropriate for a single TUAV can be significantly higher than less sophisticated sensors suitable for deployment on a group, or swarm, of coordinated TUAVs. Employing two or more coordinated TUAVs with less complex sensors may lead to an equivalent or even better CID call than sending a single TUAV with more sophisticated sensors at a significantly higher cost. In addition, the coordinated TUAVs may be capable of reducing the time needed to correctly discriminate an object.

Five measures of performance (accuracy, number of TUAVs shot down, TUAV preparation time, mean of decision time, mean of simulated mission time) from the simulation models are collected to compare the swarm system to the single TUAV system. Statistical comparisons are conducted using a paired t-test. The results illustrate improved performance of our swarm systems across most measures of performance.

15. SUBJECT TERMS
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